

## Week 3: Friday, Sep 7

### Logistics

1. HW 1 may be submitted on CMS (by midnight) or as hard copy (by lecture). The programming is pretty trivial for this one, so MATLAB fragments in your write-up are fine – no need to submit separate m-files.
2. If you're still thinking about how to generate random matrices for Problem 1, try 'help rand' and 'help sprand'. Note that just as 'sparse' converts a full matrix into sparse format, 'full' converts a sparse matrix into dense format.
3. Last lecture is *not* the last time we will be visiting the SVD – I know I went a little fast, but don't worry if you didn't get it all the first time.

### Better multiplying through structure

Consider the matrices whose elements are as follows.

1.  $A_{ij}^{(1)} = x_i y_j$  for vectors  $x, y \in \mathbb{R}^n$ .
2.  $A_{ij}^{(2)} = x_i + y_j$ .
3.  $A_{ij}^{(3)} = 1$  if  $i + j$  even, 0 otherwise.
4.  $A_{ij}^{(4)} = 1$  if  $j = \pi(i)$  for some permutation  $\pi$ .
5.  $A_{ij}^{(5)} = \delta_{ij} + x_i y_j$ .
6.  $A_{ij}^{(6)} = \mu^{|i-j|}$ .

The questions:

1. How can we write a fast ( $O(n)$ ) algorithm to compute  $v = Au$  for each of these matrices?
2. Given general nonsingular  $B$  and  $C$ , can we write a fast algorithm to multiply by  $\hat{A} = BAC$  in  $O(n)$  time (assuming some precomputation is allowed)?

3. Given a general nonsingular  $B$ , can we write a fast multiplication algorithm for  $\tilde{A} = B^{-1}AB$ ?

The first three matrices are all low-rank. The first matrix can be written as an outer product  $A^{(1)} = xy^T$ ; the second matrix is  $A^{(2)} = xe^T - ey^T$ , where  $e$  is the vector of all ones; and the third matrix is  $A^{(3)} = e_{\text{odd}}e_{\text{odd}}^T + e_{\text{even}}e_{\text{even}}^T$ , where  $e_{\text{odd}}$  is the vector with ones in all odd-index entries and zeros elsewhere, and  $e_{\text{even}}$  is the vector with ones in all even-index entries. We can write efficient MATLAB functions to multiply by each of these matrices:

```
% Compute v = A1*u = (x*y')*u
function v = multA1(u,x,y)
v = x*(y'*u);
```

```
% Compute v = A2*u
function v = multA2(u,x,y)
v = x*sum(u)+y'*u;
```

```
% Compute v = A3*u
function v = multA3(u);
v = zeros(length(u),1);
v(1:2:end) = sum(u(1:2:end));
v(2:2:end) = sum(u(2:2:end));
```

Note that all we are *really* using in these routines is the fact that the underlying matrices are low rank. The rank is a property of the underlying linear transformation, independent of basis; that is,  $\text{rank}(A) = \text{rank}(BAC)$  for any nonsingular  $B$  and  $C$ . So we can still get a fast matrix multiply for  $\hat{A}^{(1)} = BA^{(1)}C$ , for example, by precomputing  $\hat{x} = Bx$  and  $\hat{y} = C^T y$  and then writing  $\hat{A}^{(1)} = \hat{x}\hat{y}^T$ .

The fourth matrix just shuffles the entries of the input vector, which is trivial in MATLAB.

```
% Compute v = A4*u, A4(i,j) = 1 if j = p(i), 0 otherwise
% This means v(i) = u(p(i));
function v = multA4(v,p)
v = u(p);
```

Applying this matrix requires *no* arithmetic, but it does require  $O(n)$  index lookups and element copies. This is a prototypical example of a *sparse* matrix – one in which most of the matrix elements are zero – but the sparse structure is completely destroyed when we change the basis.

The fifth matrix is an identity plus a low-rank matrix:  $A^{(5)} = I + xy^T$ . This structure is destroyed if we change bases independently for the domain and range space (i.e.,  $BA^{(5)}C$  has no useful structure), but it is preserved when we make the same change of basis for both the domain and range (i.e.,  $B^{-1}A^{(5)}B = I + \hat{x}\hat{y}^T$ , where  $\hat{x} = B^{-1}x$  and  $\hat{y} = B^T y$ ).

The sixth matrix is much more interesting. Though the matrix does not have lots of zeros and is not related in an obvious way to something with low rank, there is nonetheless enough structure for us to do a fast multiply. Writing each entry of  $v = A^{(4)}u$  in component form, we have

$$v_j = \sum_{i=1}^n \mu^{|i-j|} u_i = \left( \sum_{i=1}^{j-1} \mu^{j-i} u_i \right) + \left( \sum_{i=j}^n \mu^{i-j} u_i \right) = r_j + l_j.$$

where  $r_j$  and  $l_j$  refer to the parts of the dot product to the right and left of the main diagonal, respectively. Now notice that

$$\begin{aligned} r_1 &= 0 \\ l_n &= u_n \\ r_{j+1} &= \mu(r_j + u_j) \\ l_j &= \mu l_{j+1} + u_j. \end{aligned}$$

The following MATLAB code runs to compute the matrix-vector product with  $A^{(6)}$  in  $O(n)$  time:

```
% Compute v=A6*u
function v = multA6(u,mu);
n = length(u);

% Run the recurrence for r forward
r = zeros(n,1);
for j = 1:n-1
    r = (r+u(j)) * mu;
end
```

```
% Run the recurrence for l backward
l = zeros(n,1);
l(n) = u(n);
for j = n-1:-1:1
    l(j) = l(j+1)*mu + u(j);
end

v = l+r;
```

There is no fast multiply for  $B^{-1}A^{(6)}B$ , let alone for  $BA^{(6)}C$ .

## Nonzero structure

One important type of structure in matrices involves where there can be nonzeros. For example, a *lower triangular*  $L$  matrix satisfies  $l_{ij} = 0$  for  $j > i$ . If we put crosses where there can be nonzeros, we have

$$L = \begin{bmatrix} \times & & & & \\ \times & \times & & & \\ \times & \times & \times & & \\ \vdots & \vdots & \vdots & \ddots & \\ \times & \times & \times & \dots & \times \end{bmatrix}.$$

Similarly, an upper triangular matrix  $U$  satisfies  $u_{ij} = 0$  for  $j < i$ . A *banded* matrix has zeros outside some distance of the diagonal; that is,  $B$  is banded with lower bandwidth  $p$  and upper bandwidth  $q$  if  $b_{ij} = 0$  for  $j < i - p$  and  $j > i + q$ . For example, a matrix with lower bandwidth 1 and upper bandwidth 2 has this nonzero structure:

$$B = \begin{bmatrix} \times & \times & \times & & & & \\ \times & \times & \times & \times & & & \\ & \times & \times & \times & \times & & \\ & & \times & \times & \times & \times & \\ & & & \ddots & \ddots & \ddots & \ddots \\ & & & & \times & \times & \times & \times \\ & & & & & \times & \times & \times \\ & & & & & & \times & \times \end{bmatrix}.$$

A banded matrix with  $b + q \ll n$  is a special case of a *sparse* matrix in which most of the elements are zero.

Why do we care about these matrix structures? One reason is that we can use these structures to improve the performance of matrix multiplication. If  $\text{nnz}$  is the number of nonzeros in a matrix, then matrix-vector multiplication can be written to take  $O(\text{nnz})$  time. We can also represent the matrix using  $O(\text{nnz})$  storage. Another reason is that some structures are easy to compute with. For example, if we want to solve a linear system with a triangular matrix, we can do so easily using back-substitution; and if we want the eigenvalues of a triangular matrix, we can just read the diagonal.

## Compact storage

How do we represent triangular matrices, banded matrices, and general sparse matrices on the computer? Recall that the conventional storage schemes for dense matrix store one column after the other (column-major storage, used by MATLAB and Fortran) or one row after the other (row-major order, used by C). For example, the matrix

$$A = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix}$$

is stored in four consecutive memory locations as

$$[1 \ 2 \ 3 \ 4],$$

assuming we are using column-major format. To store triangular, banded, and sparse matrices in compact form, we will again lay out the column entries one after the other — but we will leave out zero elements. For example, consider a banded matrix with lower bandwidth 1 and upper bandwidth 2:

$$B = \begin{bmatrix} 1 & 3 & 6 & & & \\ 2 & 4 & 7 & 10 & & \\ & 5 & 8 & 11 & 14 & \\ & & 9 & 12 & 15 & 18 \\ & & & 13 & 16 & 19 & 22 \\ & & & & 17 & 20 & 23 \\ & & & & & 21 & 24 \end{bmatrix}.$$

Each column of this matrix contains at most  $p+1+1 = 4$  nonzeros, with the first few and last few columns as exceptions. We get rid of these exceptions by conceptually padding the matrix with zero rows:

$$\begin{bmatrix} 0 & & & & & & \\ 0 & 0 & & & & & \\ \hline 1 & 3 & 6 & & & & \\ 2 & 4 & 7 & 10 & & & \\ & 5 & 8 & 11 & 14 & & \\ & & 9 & 12 & 15 & 18 & \\ & & & 13 & 16 & 19 & 22 \\ & & & & 17 & 20 & 23 \\ & & & & & 21 & 24 \\ \hline & & & & & & 0 \end{bmatrix}.$$

With the extra padding, we have exactly four things to store for each column. Think of putting these elements into a data structure  $B.\text{band}$ :

$$B.\text{band} = \begin{bmatrix} 0 & 0 & 6 & 10 & 14 & 18 & 22 \\ 0 & 3 & 7 & 11 & 15 & 19 & 23 \\ 1 & 4 & 8 & 12 & 16 & 20 & 24 \\ 2 & 5 & 9 & 13 & 17 & 21 & 0 \end{bmatrix}.$$

The  $B.\text{band}$  structure would typically then be laid out in memory in column-major order.

The details of multiplying by a band matrix were not covered in lecture, but they are in the book.

What if we have relatively few nonzeros in a matrix, but they are not in a narrow band about the origin or some other similarly regular structure? In this case, we would usually represent the matrix by a general sparse format. The format MATLAB uses internally is *compressed sparse columns*. In compressed sparse column format, we keep a list of the nonzero entries and their corresponding rows, stored one column after the other; and a list of pointers saying where the data for each column starts. For example, consider the matrix

$$A = \begin{bmatrix} a_{11} & 0 & 0 & a_{14} \\ 0 & a_{22} & 0 & 0 \\ a_{31} & 0 & a_{33} & 0 \\ 0 & a_{42} & 0 & a_{44} \end{bmatrix}.$$

In compressed sparse column form, we would have

		1	2	3	4	5	6	7
entries	=	$a_{11}$	$a_{31}$	$a_{22}$	$a_{42}$	$a_{33}$	$a_{14}$	$a_{44}$
rows	=	1	3	2	4	3	1	4
column pointers	=	1	3	6	8			

The last entry in the column pointer array tells is there to indicate where the *end* of the last column is. Fortunately, if you are using MATLAB, the details of this data structure are hidden from you. To get a sparse representation of a matrix  $A$  is as simple as writing

```
As = sparse(A);
```