

# Matricies and Vectors

COMP2611: Data Structures  
2019

# Outline

- ▶ Basic Definitions
- ▶ Sparse Matrices
  - ▶ DOK, LIL, COO, CSR, CSC
- ▶ Special square matrices
  - ▶ Lower Triangular
  - ▶ Upper Triangular
  - ▶ Symmetric

# What are Matrices?

- ▶ Rectangular array (2D array) of numbers or expressions. We call this a rank 2 tensor
- ▶ If a matrix has ***n*** rows and ***m*** cols, we call it an ***n* × *m*** matrix. We call these the matrix's dimensions

$$A = \begin{bmatrix} 2 & 3 & 4 \\ 5 & 6 & 7 \end{bmatrix}$$

*A* is a 2 × 3 matrix



# What are Matrices

- ▶ Each number or expression in the matrix is called an element or component
- ▶ Matrices are indexed by their rows and columns
  - ▶ Each element can be identified by a row, column pair
  - ▶ Matrices are typically **1**-indexed in Maths, but we implement using **0**-indexing. Need to translate between the two!
- ▶ E.g.  $\mathbf{A}_{1,2}$  refers to the entry of matrix  $\mathbf{A}$  at row **1**, column **2**. From the last slide,  $\mathbf{A}_{1,2} = 3$

# Matricies in Programming

Python

```
A = [  
    [2, 3, 4],  
    [5, 6, 7]  
]
```

C++

```
float A[][] = {  
    {2, 3, 4},  
    {5, 6, 7}  
};
```

In Both of these languages,  $A_{1,2}$  is at `A[0][1]`  
Implemented as arrays of arrays

# Vector

- ▶ Special shapes of matrices where we have either **1** row or **1** column.
- ▶ Since we know that it has only a single column or row, we usually use a single index to identify a value when writing expressions mathematically.
- ▶ Depending on implementation, we still need both indexes when programming



# Column Vectors

- ▶ Vectors where we have **1** column
- ▶ Usually we take column vectors as default
- ▶ When Maths textbooks say vector, translate to column vector!

$$v = \begin{bmatrix} 2 \\ 3 \\ 4 \end{bmatrix}$$

$$v_3 = 4$$

# Row Vectors

- ▶ Vectors with one row
- ▶ Regular single-dimensional arrays are seen as row vectors in many implementations
- ▶ Not the default in Maths though

$$w = [4 \quad 5 \quad 6]$$

$$w_2 = 5$$



# Why Care About Matrices and Vectors?

- ▶ Primary objects of study in Linear Algebra - field of Mathematics
- ▶ Linear Algebra is important in the sciences and engineering
- ▶ CS is a field of Maths, Science, and Engineering
  - ▶ Should care be default!
- ▶ On the applied side Linear Algebra is part of reason behind computer's increased popularity

# Why Care About Matrices and Vectors?

- ▶ Fortran was designed with Linear Algebra in mind!
- ▶ Matrices and Vectors used throughout CS:
  - ▶ Machine Learning
  - ▶ Simulation
  - ▶ Computer Modelling
  - ▶ Bioinformatics
  - ▶ Computer Graphics
  - ▶ Optimization
  - ▶ Game Programming, etc ...

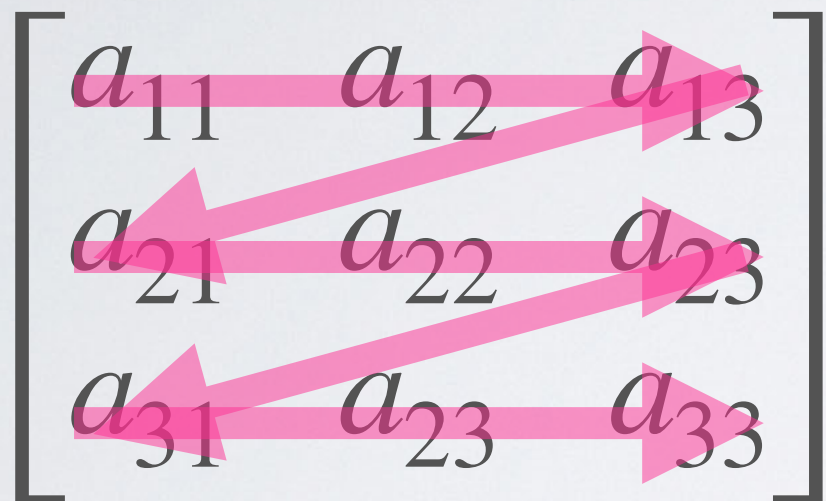
# Libraries for Linear Algebra

- ▶ BLAS - Basic Linear Algebra Subroutines
- ▶ LAPACK - Linear Algebra Package
- ▶ Foundation for most other linear algebra libraries
  - ▶ Called using Foreign Function Interface (FFI)
- ▶ Other examples include:
  - ▶ Armadillo (C++)
  - ▶ NumPy (Python)
  - ▶ Julia - standard library
  - ▶ MATLAB - standard library

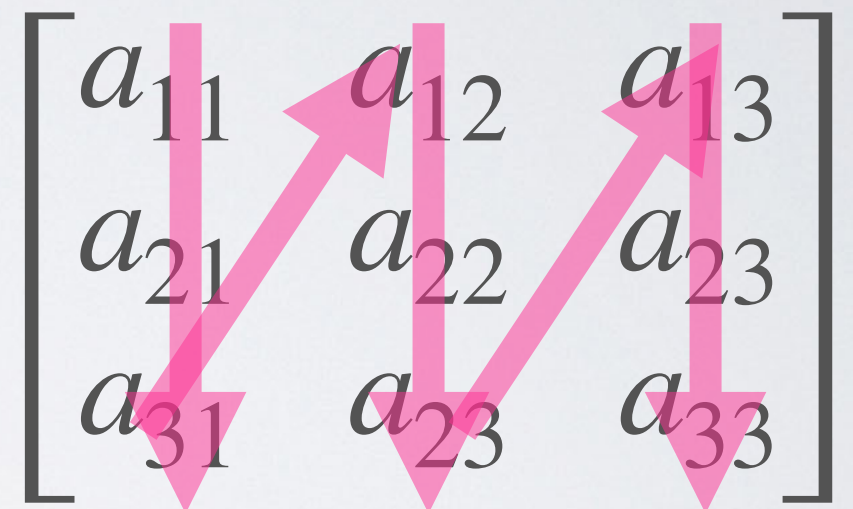


# MAJOR ORDERS

Row major order  
(Raster format)



Column major order



# Some Operations on Matrices and Vectors

- ▶ Many operations, some include:
- ▶ Component-wise addition
  - ▶ Only if dimensions match
- ▶ Component-wise multiplication (Hadamard product)
  - ▶ Only if dimensions match
- ▶ Transpose
- ▶ Scalar Multiplication
- ▶ Matrix-Matrix multiplication
  - ▶ Dimensions must **agree**
  - ▶ Matrix-vector multiplication
  - ▶ Affine Transformation

# Some Operations on Matrices and Vectors

- ▶ Many operations, some include:
- ▶ Component-wise addition
  - ▶ Only if dimensions match
- ▶ Component-wise multiplication (Hadamard product)
  - ▶ Only if dimensions match
- ▶ **Transpose**
- ▶ Scalar Multiplication
- ▶ **Matrix-Matrix multiplication**
  - ▶ Dimensions must **agree**
  - ▶ Matrix-vector multiplication
  - ▶ Affine Transformation



# Transpose

- ▶ If  $\mathbf{A}$  is a matrix (or vector) its transpose is written as  $\mathbf{A}^T$
- ▶ “Make rows columns”

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$$

$$A^T = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix}$$

# Tranpose Pseudocode

```
function transpose(A)
    num_rows = length(A)
    num_cols = length(A[0])
    A_t = create_array((num_cols, num_rows))
    for i = 0 to num_rows - 1:
        for j = 0 to num_cols - 1:
            A_t[j][i] = A[i][j]
    return A_t
```

# Matrix Multiplication

- ▶ Important, but expensive operation
- ▶ Technically a form of function composition on linear transformation
- ▶ “Row into column”
- ▶ If  $\mathbf{A}$  and  $\mathbf{B}$  are matrices with dimensions  $\mathbf{p} \times \mathbf{q}$  and  $\mathbf{q} \times \mathbf{r}$  respectively , and  $\mathbf{C} = \mathbf{A} \cdot \mathbf{B}$ , then

$$C_{i,j} = \sum_{k=1}^q A_{i,k} \cdot B_{k,j}$$



# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} ? & ? \\ ? & ? \end{bmatrix}$$

# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 1 \cdot 4 + 2 \cdot 6 + 3 \cdot 8 & ? \\ ? & ? \end{bmatrix}$$

# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 40 & ? \\ ? & ? \end{bmatrix}$$



# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 40 & 1 \cdot 5 + 2 \cdot 7 + 3 \cdot 9 \\ ? & ? \end{bmatrix}$$

# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 40 & 46 \\ ? & ? \end{bmatrix}$$

# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} & 40 & 46 \\ 4 \cdot 4 + 5 \cdot 6 + 6 \cdot 8 & ? \end{bmatrix}$$



# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 40 & 46 \\ 94 & ? \end{bmatrix}$$

# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 40 & 46 \\ 94 & 4 \cdot 5 + 5 \cdot 7 + 6 \cdot 9 \end{bmatrix}$$

# Matrix Multiplication

- ▶ number of columns in the 1st matrix = number of rows in the 2nd

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 4 & 5 \\ 6 & 7 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 40 & 46 \\ 94 & 109 \end{bmatrix}$$



# Matrix Multiplication Pseudocode

```
function matrix_mult(A, B)
    num_rows = length(A)
    num_cols = length(A[0])
    num_rows1 = length(B)
    num_cols1 = length(B[0])
    if num_cols != num_rows1:
        error()
    C = create_array((num_rows, num_cols1))
    fill_array(C, 0)
    for i = 0 to num_rows - 1:
        for j = 0 to num_cols1 - 1:
            for k = 0 to num_rows1 - 1:
                C[i][j] = A[i][k] * B[k][j]
    return C
```

# Matrix Multiplication

- ▶ if  $n = \max(p, q, r)$ , then this algorithm is  $O(n^3)$
- ▶ Expensive for large  $n$
- ▶ Approximation algorithms and parallelism used in practice to perform matrix multiplication

# Sparse Matrices

- ▶ Matrix multiplication is the backbone of many algorithms using matrices
- ▶ Matrix multiplication, as we just saw, is expensive
- ▶ A matrix where most entries are **0** is called a sparse matrix
- ▶ What happens if most of our matrix is **0**?



# Sparse Matrix Multiplication

$$\begin{bmatrix} 1 & 0 & 3 \\ 4 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0 & 5 \\ 0 & 0 \\ 8 & 0 \end{bmatrix} = \begin{bmatrix} ? & ? \\ ? & ? \end{bmatrix}$$

# Sparse Matrix Multiplication

$$\begin{bmatrix} 1 & 0 & 3 \\ 4 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0 & 5 \\ 0 & 0 \\ 8 & 0 \end{bmatrix} = \begin{bmatrix} 1 \cdot 0 + 0 \cdot 0 + 3 \cdot 8 & 1 \cdot 5 + 0 \cdot 0 + 3 \cdot 0 \\ 4 \cdot 0 + 0 \cdot 0 + 0 \cdot 8 & 4 \cdot 5 + 0 \cdot 0 + 0 \cdot 0 \end{bmatrix}$$

# Sparse Matrix Multiplication

$$\begin{bmatrix} 1 & 0 & 3 \\ 4 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0 & 5 \\ 0 & 0 \\ 8 & 0 \end{bmatrix} = \begin{bmatrix} 24 & 5 \\ 0 & 20 \end{bmatrix}$$



# Sparse Matrices

- ▶ Matrix multiplication becomes “simpler” if most entries are 0s.
- ▶ All of these 0s are stored, yet have no effect on outcomes
  - ▶ This is wasted space
- ▶ Different ways to store sparse matrices to minimise space wastage and make write faster algorithms
- ▶ Some are better under some circumstances than others

# Sparse Matrix Representations

- ▶ DOK - Dictionary of Keys
- ▶ LIL - List of Lists
- ▶ COO - Coordinate List
- ▶ CSR - Compressed Sparse Row
- ▶ CSC - Compressed Sparse Column

# Dictionary of keys

- ▶ Store only non-zero entries in a dictionary
  - ▶ Keys are coordinates (indices)
  - ▶ Values are the entries
- ▶ Fine for addition, scalar multiplication, and hadamard product
- ▶ Not that great for matrix multiplication
- ▶ Great as intermediary between other formats and great for direct access of entries



```
function mat_to_dok(A)
    D = create_dict()
    num_rows = length(A)
    num_cols = length(A[0])
    for i = 0 to num_rows - 1:
        for j = 0 to num_cols - 1:
            if A[i][j] != 0:
                insert(D, (str(i)+", "+str(j)), A[i][j])
    return D
```

Key

Value

```
function mat_to_dok(A)
    D = create_dict()
    num_rows = length(A)
    num_cols = length(A[0])
    for i = 0 to num_rows - 1:
        for j = 0 to num_cols - 1:
            if A[i][j] != 0:
                insert(D, (str(i)+", "+str(j)), A[i][j])
    return D
```

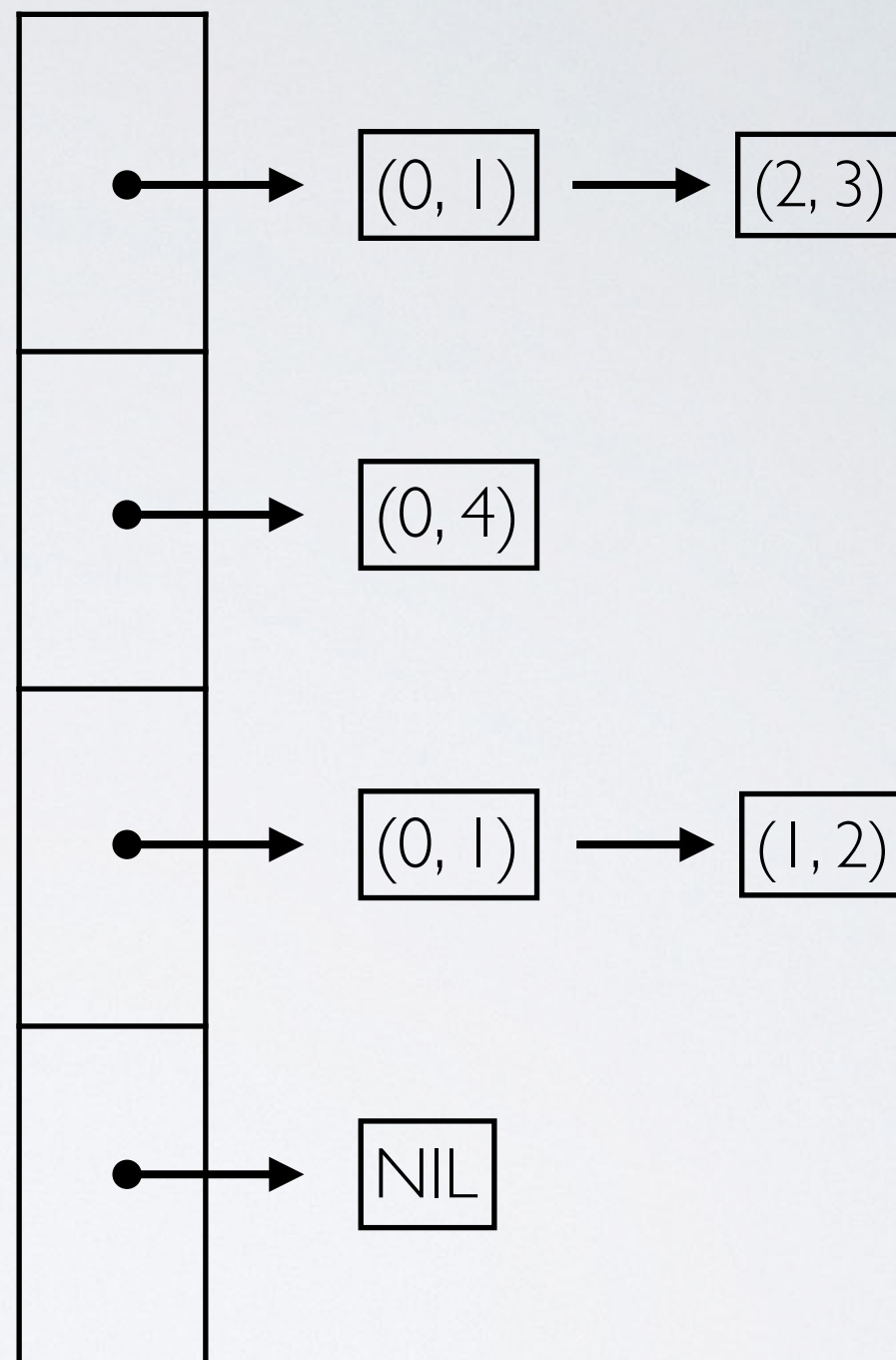
```
function dok_get_entry(D, i, j)
    key = str(i) + "," + str(j)
    value = search(D, key)
    if value == NIL:
        return 0
    return value
```



# LIL

- ▶ Store only non-zero entries in a jagged 2D array or an array of link lists
  - ▶ jagged 2D array is an array of arrays
  - ▶ inner arrays need not be the same length
  - ▶ each inner array associated with a row
  - ▶ each entry in LIL comprises of (col, entry) pair sorted by col
- ▶ Good for addition and scalar multiplication
- ▶ Not that great for matrix multiplication
- ▶ Great as intermediary between other formats and good for direct access of entries (have some searching for entry)

$$A = \begin{bmatrix} 1 & 0 & 3 \\ 4 & 0 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$



```
function mat_to_lil(A)
    L = create_array()
    num_rows = length(A)
    num_cols = length(A[0])
    for i = 0 to num_rows - 1:
        L.append(create_array())
    for i = 0 to num_rows - 1:
        for j = 0 to num_cols - 1:
            if A[i][j] != 0:
                L[i].append((j, A[i][j]))
    return L
```



```
function lil_get_entry(L, i, j)
    l = L[i]
    for (col, entry) in l:
        if col == j:
            return entry
        elif col > j:
            break
    return 0
```

# COO

- ▶ Store non-zero entries as sorted array of triples
  - ▶ Each triple contains (row, col, entry)
  - ▶ Sorted by row, then by col if rows are equal
- ▶ Can use binary search for retrieval
- ▶ Good as intermediary format

$$A = \begin{bmatrix} 1 & 0 & 3 \\ 4 & 0 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

(0, 0, 1)	(0, 2, 3)	(1, 0, 4)	(2, 0, 1)	(2, 1, 2)
-----------	-----------	-----------	-----------	-----------



```
function mat_to_coo(A)
    L = create_array()
    num_rows = length(A)
    num_cols = length(A[0])
    for i = 0 to num_rows - 1:
        for j = 0 to num_cols - 1:
            if A[i][j] != 0:
                L.append((i, j, A[i][j]))
    return L
```

```
function cmp(i1, j1, i2, j2)
    if i1 == i2:
        if j1 == j2:
            return 0
        return (j1 > j2) ? 1: -1
    return (i1 > i2) ? 1: -1
```

```
function coo_get_entry(L, i, j)
    lo = 0
    hi = length(L) - 1
    while hi >= lo:
        mid = (hi + lo) / 2
        (i2, j2, entry) = L[mid]
        if cmp(i, j, i2, j2) == 0:
            return entry
        if cmp(i, j, i2, j2) > 1:
            hi = mid - 1
        else:
            lo = mid + 1
    return 0
```

# Yale Formats

- ▶ CSR and CSC are two versions of the Yale formats of sparse matrix representation
- ▶ Use three arrays to store non-zero entries
- ▶ **Best** format for sparse matrix multiplication
- ▶ **Great** for splicing across rows (CSR) or columns (CSC)



# Yale Formats

- ▶ Both CSR and CSC use three arrays:
  - ▶ **A** - stores the non-zero entries
  - ▶ **IA** - recursively defined as follows
    - ▶  $IA[0] = 0$
    - ▶  $IA[i] = IA[i - 1] + (\text{num non-zero elements in } i-1 \text{ row (CSR) or column (CSC)})$
  - ▶ **JA** - stores the column index (CSR) or row index (CSC) of the entries in A
- ▶  $A[IA[i]]$  to  $A[IA[i+1] - 1]$  hold the entries from row **i** (CSR) or column **i** (CSC)

$$M = \begin{bmatrix} 1 & 0 & 3 \\ 4 & 0 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$A = [1 \quad 3 \quad 4 \quad 1 \quad 2]$$

$$IA = [0 \quad 2 \quad 3 \quad 5 \quad 5 \quad 5]$$

$$JA = [0 \quad 2 \quad 0 \quad 0 \quad 1]$$

$$A = [1 \quad 3 \quad 4 \quad 1 \quad 2]$$

$$IA = [0 \quad 3 \quad 4 \quad 5]$$

$$JA = [0 \quad 0 \quad 1 \quad 2 \quad 2]$$

```
function mat_to_csr(M)
  A = create_array()
  IA = create_array()
  IA.append(0)
  JA = create_array()
  num_rows = length(A)
  num_cols = length(A[0])
  for i = 0 to num_rows - 1:
    count = 0
    for j = 0 to num_cols - 1:
      if A[i][j] != 0:
        A.append(A[i][j])
        JA.append(j)
        count += 1
    IA.append(last_element(IA) + count)
  return A, IA, JA
```



```
function row_slice_csr(A, IA, i)  
    return A[IA[i]:(IA[i + 1] - 1)]
```

```
function get_entry_csr(A, IA, JA, i, j)  
    starting_index = IA[i]  
    ending_index = IA[i + 1] - 1  
    for k = starting_index to ending_index:  
        if JA[k] == j:  
            return A[k]  
    return 0
```

Will look at CSC in Lab. Should try implementing on your own first

# Other Special Matrices

- ▶ A matrix with the same number of rows and columns is called a square matrix
- ▶ There are special types of square matrices:
  - ▶ Triangular
    - ▶ Upper and Lower
  - ▶ Symmetric

# Triangular Matrices

- ▶ Either the upper half or lower half is completely filled

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix}$$

Upper triangular

$$\begin{bmatrix} 0 & 0 & a_{13} \\ 0 & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

Lower triangular



# Storing Triangular Arrays

- ▶ Can store using a single array. Map 2D index to 1D

- ▶ Array contains  $\sum_{i=1}^n i$  entries

- ▶  $\sum_{i=1}^n i = \frac{1}{2}n(n+1)$

# Lower Triangular

- ▶ How do we map 2D indices to 1D?
- ▶ Use AP
- ▶ If we want entry at  $(i, j)$  we need to move past all elements before index  $i$ . The entry at  $(i, j)$  is then  $j$  positions away

$$\begin{bmatrix} 0 & 0 & 3 \\ 0 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \quad [3 \ 5 \ 6 \ 7 \ 8 \ 9]$$

# Lower Triangular

$$\triangleright \text{index}(i, j) = (j - 1) + \sum_{p=1}^i p$$

$$\triangleright \text{index}(i, j) = (j - 1) + \frac{1}{2}i(i + 1)$$

$$\begin{bmatrix} 0 & 0 & 3 \\ 0 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \quad [3 \ 5 \ 6 \ 7 \ 8 \ 9]$$



# Upper Triangular

- ▶ Reverse situation of Lower triangular
- ▶ If we want entry at  $(i, j)$  we need to move past all elements such that we have index  $i + (i - 1) + (i - 2) + \dots + 1$  entries left. The entry at  $(i, j)$  is then  $j$  positions away

$$\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 6 \\ 0 & 0 & 9 \end{bmatrix} \quad [1 \quad 2 \quad 3 \quad 5 \quad 6 \quad 9]$$

# Upper Triangular

$$\begin{aligned} \text{index}(i, j) &= (j - 1) + \left( \sum_{p=1}^n p \right) - \sum_{p=1}^i p \\ \text{index}(i, j) &= (j - 1) + \frac{1}{2}n(n + 1) - \frac{1}{2}i(i - 1) \end{aligned}$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 6 \\ 0 & 0 & 9 \end{bmatrix}$$

$$[1 \ 2 \ 3 \ 5 \ 6 \ 9]$$

$n$  is the dimension

# Returning 0s

- ▶ If Upper triangular where  $j$  is the column and  $i$  is the row, if  $j > i$ , then return 0
- ▶ If Lower triangular where  $j$  is the column and  $i$  is the row, if  $j < i$ , then return 0



# Symmetric Matrices

- ▶ Both half of the matrix are the same
- ▶ The transpose of such a matrix is itself
- ▶ Examples: any undirected graph
- ▶ Store as Lower Triangular
  - ▶ Except if we query  $j < i$ , return the same entry at `index(i, j)`