

10. Matrix multiplication

10.1. Matrix-matrix multiplication

In Python the product of matrices A and B is obtained with $A @ B$. Alternatively, we can compute the matrix product using the function `np.matmul()`. We calculate the matrix product on page 177 of VMLS.

```
In [ ]: A = np.array([[ -1.5, 3, 2], [1, -1, 0]]) #2 by 3 matrix
        B = np.array([[ -1, -1], [0, -2], [1, 0]]) #3 by 2 matrix
        C = A @ B
        print(C)
```

```
[[ 3.5 -4.5]
```

```
In [ ]: [-1.  1. ]
        C = np.matmul(A,B)
        print(C)
```

```
[[ 3.5 -4.5]
 [-1.  1. ]
```

Gram matrix. The Gram matrix of a matrix A is the matrix $G = A^T A$. It is a symmetric matrix and the i, j element $G_{i,j}$ is the inner product of columns i and j of A .

```
In [ ]: A = np.random.normal(size = (10,3))
        G = A.T @ A
        print(G)
```

```
[[ 8.73234113 -2.38507779  1.59667064]
 [-2.38507779  3.07242591  0.49804144]
 [ 1.59667064  0.49804144 15.65621955]]
```

```
In [ ]: #Gii is norm of column  $i$ , squared
        G[1,1]
```

10. Matrix multiplication

```
Out [ ]: 3.072425913055046
```

```
In [ ]: np.linalg.norm(A[:,1])**2
```

```
Out [ ]: 3.072425913055046
```

```
In [ ]: #Gij is inner product of columns i and j  
G[0,2]
```

```
Out [ ]: 1.5966706354935412
```

```
In [ ]: A[:,0] @ A[:,2]
```

```
Out [ ]: 1.5966706354935412
```

Complexity of matrix triple product. Let's check the associative property, which states that $(AB)C = A(BC)$ for any $m \times n$ matrix A , any $n \times p$ matrix B , and any $p \times q$ matrix C . At the same time we will see that the left-hand and right-hand sides take very different amounts of time to compute.

```
In [ ]: import time  
m = 2000  
n = 50  
q = 2000  
p = 2000  
A = np.random.normal(size = (m,n))  
B = np.random.normal(size = (n,p))  
C = np.random.normal(size = (p,q))  
start = time.time()  
LHS = (A @ B) @ C  
end = time.time()  
print(end - start)
```

```
0.17589497566223145
```

```
In [ ]: start = time.time()  
LHS = (A @ B) @ C  
end = time.time()  
print(end - start)
```

```
0.23308205604553223
```

10.2. Composition of linear functions

```
In [ ]: start = time.time()
        RHS = A @ (B @ C)
        end = time.time()
        print(end - start)
```

```
0.026722192764282227
```

```
In [ ]: start = time.time()
        RHS = A @ (B @ C)
        end = time.time()
        print(end - start)
```

```
0.025452852249145508
```

```
In [ ]: np.linalg.norm(LHS - RHS)
```

```
Out[ ]: 4.704725926477414e-10
```

```
In [ ]: start = time.time()
        D = A @ B @ C      #Evaluated as (A@B)@C or as A@(B@C)?
        end = time.time()
        print(end - start)
```

```
0.24454998970031738
```

From the above, we see that evaluating $(A@B)@C$ takes around 10 times as much time as evaluating $A@(B@C)$, which is predicted from the complexities. In the last line, we deduce that $A@B@C$ is evaluated left to right, as $(A@B)@C$. Note that for these particular matrices, this is the (much) slower order to multiply the matrices.

10.2. Composition of linear functions

Second difference matrix. We compute the second difference matrix on page 184 of VMLS.

```
In [ ]: D = lambda n: np.c_[-np.identity(n-1), np.zeros(n-1)] +
        ↪ np.c_[np.zeros(n-1), np.identity(n-1)]
        D(5)
```

```
Out[ ]: array([[ -1.,  1.,  0.,  0.,  0.],
               [  0., -1.,  1.,  0.,  0.],
               [  0.,  0., -1.,  1.,  0.]])
```