ML Assignment 2

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```
In [1]:
```

```
import numpy as np
import time
import random
```

Properties of Matrix Multiplication

```
In [2]:
```

```
A=np.array([[np.random.randint(0,100) for j in range(10)] for i in range(10)])
B=np.array([[np.random.randint(0,100) for j in range(10)] for i in range(10)])
C=np.array([[np.random.randint(0,100) for j in range(10)] for i in range(10)])
```

```
In [3]:
```

```
def proof(A,B):
    if A.shape!=B.shape:
        return False
    else:
        for i in range(A.shape[0]):
            for j in range(A.shape[1]):
                if A[i][j]!=B[i][j]:
                      return False
        return True
```

Associative Property

A(BC) = (AB)C

```
In [4]:
```

```
a=np.matmul(A,np.matmul(B,C))
b=np.matmul(np.matmul(A,B),C)
if proof(a,b):
    print("Matrices are Associative!")
else:
    print("Matrices are not Associative!")
```

Matrices are Associative!

Distributive Property

```
A(B + C) == (AB) + (AC)
```

```
In [5]:
```

```
abc=np.matmul(A, np.add(B,C))
abac=np.add(np.matmul(A,B), np.matmul(A,C))
if proof(abc,abac):
    print("Matrices are Distributive!")
else:
    print("Matrices are not Distributive!")
```

Matrices are Distributive!

Non-commutative property

AB != BA

```
In [6]:
```

```
ab=np.matmul(A,B)
ba=np.matmul(B,A)
if proof(ab,ba):
    print("Matrices are Commutative!")
else:
    print("Matrices are Non-Commutative!")
```

Matrices are Non-Commutative!

Inverse of matric using numpy:

```
In [7]:
a inv=np.linalq.inv(A)
print(a_inv)
[[-5.13352330e-03 3.87356311e-04 -9.53691044e-03 6.09746269e-03
  1.30413324e-02 3.57543243e-03 -5.18533449e-03 -3.42282343e-03
  4.10707661e-03 -4.34448202e-03]
 [-1.23311614e-02 \quad 1.63077641e-05 \quad 1.83806117e-02 \quad -1.35927767e-02
 -2.65199406e-02
                 7.88960805e-03 9.63436698e-03 -4.85689867e-03
 -1.69111057e-02 3.31634715e-02]
 [-3.80340198e-03 4.85466659e-03 -8.93138632e-03 5.43535571e-03
 -8.02470912e-06 -4.48258320e-03 3.22295240e-04 7.17410523e-03
 -1.25562221e-03 1.89037170e-03]
 [ 3.51328689e-03 -2.25134957e-03 1.14290539e-02 -7.63366738e-03
 -8.36715663e-03 -1.33551846e-02 8.99071841e-03 -4.66080139e-04
 -6.97237910e-03 1.84890187e-02]
 9.29921972e-03 2.33496711e-03 -8.58362475e-03 -3.94644500e-03
  1.40574177e-02 -1.58383146e-021
 1.08172055e-02 -1.55715324e-03 4.23897036e-04 1.33754290e-03
  1.45456779e-03 -1.81747170e-02]
 [-9.10236727e-03 -8.96235679e-03 7.18448201e-03 -1.52149315e-02
  -1.18549036e-02 9.31113437e-03 4.37400386e-03 5.90407226e-03
  7.15107961e-04 1.31389426e-02]
 [-1.37136359e-02 -3.54587626e-03  1.60096212e-02  1.79823770e-03
  -5.51095177e-03 -5.25609506e-03 4.40116834e-03 2.00183753e-03
 -9.71796599e-03 1.47301673e-02]
 [ 1.31788567e-03  4.97247471e-03  6.28818957e-03  4.48867610e-03
  3.21348105e-03 -2.59167774e-03 4.96717982e-03 -9.02668203e-03
  5.31995492e-03 -1.09557966e-02]
 [ 1.00059907e-02 6.15566765e-03 -1.42586346e-02 3.16673211e-03
  1.40714995e-02 5.07780693e-03 -1.32717404e-02 4.56486912e-03
  1.09342764e-02 -2.18108501e-02]]
In [8]:
b inv=np.linalg.inv(B)
print(b inv)
```

```
b_inv=np.linalg.inv(B)
print(b_inv)

[[-7.01763892e-03    8.47264346e-03    5.17212375e-04   -9.79268162e-03
    -3.76386264e-03    -3.01315165e-03    6.28173181e-03    1.01359522e-02
    -2.46158958e-03    3.48962819e-03]
[ 1.90123585e-02    -3.75770340e-02    1.76826158e-02    4.91998687e-03
    1.03891301e-03    -8.97603321e-04   -1.93498090e-02    1.01614061e-02
    7.61231877e-03    -3.27982112e-03]
[ 4.02966316e-02    -6.66176229e-02    2.95939153e-02    1.92926147e-02
```

2.65071922e-02 -2.21104152e-02 -3.81097839e-02 -2.13828742e-02

[-2.32413694e-02 3.81120764e-02 -1.33145710e-02 6.05635663e-04

8.06022952e-03 2.40397258e-02]

```
-1.6683U331e-U2 1.1U8964ZZe-UZ Z.U/ZZ86ZZe-UZ -Z.61949Z69e-U6
-3.66137465e-03 -1.40663818e-02]
[-1.69248332e-02 \quad 2.49140354e-02 \quad -7.89385989e-03 \quad -1.17242695e-02
 2.04647848e-03 8.49191500e-03 1.85026097e-02 -1.43208484e-02
-2.34305443e-03 1.71297105e-031
[ 1.58212656e-02 -1.52321836e-02 4.06817193e-03 3.42238972e-03
 -4.94004266e-04 -1.10149908e-02 -7.42374862e-04 3.03835305e-03
 2.96761769e-03 -1.14352776e-04]
[-2.46778350e-03 4.16417912e-03 -9.09456120e-03 6.87319284e-03
 3.71005657e-03 4.72361549e-04 5.97584749e-03 -2.87229812e-03
 -5.71085530e-03 4.20020000e-03]
1.63077484e-02 -2.03532659e-02 -2.07685613e-02 -6.71965071e-04
 9.01573108e-03 1.31195746e-02]
[-1.51338636e-02 3.20530755e-02 -8.12102619e-03 -8.84310100e-03
-1.00469193e-02 1.31474884e-02 1.30745632e-02 1.16184154e-02
-7.22863349e-03 -1.72639770e-02]
[-2.17245051e-02 \quad 3.75546055e-02 \quad -1.80736204e-02 \quad -1.09768273e-02
-1.16555118e-02 1.75505894e-02 1.58175612e-02 4.02874077e-03
-1.89004002e-03 -6.01822882e-0311
```

In [9]:

```
c inv=np.linalg.inv(C)
print(c_inv)
 [[\ 0.01701773\ -0.00916301\ -0.00965099\ -0.02084687\ \ 0.01278552\ \ 0.01721986
  -0.01291315 0.00534465 -0.00732402 0.02173062]
 0.02282933 0.0074117
  -0.00105287 -0.0083262 -0.01739292 0.0237761 ]
 [ \ 0.00333575 \ \ 0.00444986 \ \ 0.00383473 \ -0.00934565 \ \ 0.00653342 \ -0.00308415 ]
  -0.00470422 0.00160406 -0.00200978 0.00754495]
  \begin{bmatrix} -0.00812212 & -0.00471042 & 0.00806076 & 0.00486763 & -0.00266057 & -0.00686953 \end{bmatrix} 
   0.00826728 -0.00768912 0.01130147 -0.00974008]
  \begin{bmatrix} -0.0106018 & -0.0143301 & 0.00194375 & 0.03228707 & -0.03212923 & -0.01752799 \end{bmatrix} 
   0.0152011 0.00738566 0.02722735 -0.02678255]
 [-0.00126874 \ -0.01422495 \ -0.00262482 \ -0.00066265 \ -0.01313272 \ \ 0.00363825]
   0.00148975 0.01403641 0.00805623 0.00804478]
 [-0.01110337 \quad 0.00564731 \quad 0.00422035 \quad 0.01977089 \quad -0.02064502 \quad -0.00590279
   0.00566673 -0.0035415
                            0.01085229 -0.01422449]
 [-0.00213909 \quad 0.00628339 \quad -0.00631197 \quad 0.00105671 \quad 0.00656335 \quad -0.00074434
                0.00589427 0.00056777 -0.008492441
  -0.0015447
 [-0.00204126 \quad 0.00276393 \quad 0.00886072 \quad 0.01447631 \quad 0.00126324 \quad 0.00263172]
  -0.00832675 -0.00662879 -0.00540462 -0.01191712]
                0.02076034 0.0033177 -0.01374157 0.0194213 0.00396351
 [ 0.0066508
   0.00258667 -0.01366678 -0.02342594 0.00557933]]
```

Is Numpy faster than traditional looping?

```
In [11]:
```

```
X=np.array([[np.random.randint(0,100) for j in range(1000)] for i in range(1000)])
Y=np.array([[np.random.randint(0,100) for j in range(1000)] for i in range(1000)])
```

Traditional Looping:

```
In [13]:
```

```
start=time.time()
res=np.array([[0 for i in range(1000)] for j in range(1000)])
for i in range(X.shape[0]):
    for j in range(X.shape[1]):
        res[i][j]=X[i][j]+Y[i][j]

loop_time=time.time()-start
print(loop_time)
```

Numpy Array:

```
In [14]:
```

```
start_time=time.time()
res_np=np.add(X,Y)

np_time=time.time()-start_time
print(np_time)
```

0.004006624221801758

In []: