

Generator (dependent case - s0.99)

June 14, 2023

```
[11]: import warnings
warnings.filterwarnings('ignore')
```

```
[12]: ##### Importing packages
      <-#####

import numpy as np          # to handle arrays and matrices
import pickle

from scipy.linalg import toeplitz # to generate toeplitz matrix
from scipy.stats import chi2      # to have chi2 quantiles
from scipy.special import chdtri

import matplotlib.pyplot as plt  # to plot histograms ...
import pandas as pd             # to handle and create dataframes

from scipy.linalg import toeplitz # to generate toeplitz matrix
from scipy.stats import chi2      # to have chi2 quantiles
from scipy.special import chdtri

import time
import concurrent.futures
import random
import os

from itertools import product

##### For printing with colors #####
class color:
    PURPLE = '\033[95m'
    BLACK = '\033[1;90m'
    CYAN = '\033[96m'
    DARKCYAN = '\033[36m'
    BLUE = '\033[94m'
    GREEN = '\033[1;92m'
    YELLOW = '\033[93m'
```

```

RED = '\033[1;91m'
BOLD = '\033[1m'
UNDERLINE = '\033[4m'
END = '\033[0m'
BCKGRND = '\033[0;100m'
RBCKGRND = '\033[0;101m'

print(color.BLUE + color.BOLD + '***** Starting the program !\n
↳*****' + color.END )

```

***** Starting the program ! *****

0.1 2.1 Toeplitz Matrix

Creating a function that gets two parameters s and q such that : - s (dependency threshold or intraparameter of dispersion) - and q (the dimension) then returns a symetric toeplitz matrix S^2 that can be used as a covariance matrix for generating normal vectors

```

[13]: def cov_toep(s, q):
        """A function that takes the dependency thresholds $s$
        and the dimension $q$ and returns a $q \times q$-toeplitz matrix.
        """
        row = np.array([])
        for k in range(q):
            row = np.append(row, float(s**k))
        return toeplitz(row, row)

```

```

[14]: print(cov_toep(0.1, 4))
print()
print(cov_toep(0.99, 4))

```

```

[[1.    0.1   0.01  0.001]
 [0.1   1.    0.1   0.01 ]
 [0.01  0.1   1.    0.1   ]
 [0.001 0.01  0.1   1.    ]]

[[1.    0.99  0.9801  0.970299]
 [0.99  1.    0.99   0.9801  ]
 [0.9801 0.99  1.    0.99   ]
 [0.970299 0.9801 0.99  1.    ]]

```

```

[15]: # importing q_list, n_list, S2 diagonals, for different sigma (sigma means here
↳the std of underlying normal
# distribution that generates lognormal vectors), having the same alpha
q_list = list(pickle.load(open("q_list", "rb")))

```

```
n_list = list(pickle.load(open("n_list", "rb")))
print(q_list)
```

[50, 100, 150, 200, 250, 300, 350, 400]

```
[16]: def scalar(A,B):
        """Takes two symmetric matrices A and B of sizes q
        and returns the modified frobenius scalar of A and B
        """
        return(np.trace(A.dot(np.transpose(B)))/A.shape[0])

def norm(A):
    """Takes a symmetric matrix A of sizes q
    and returns the norm of A
    This norm is associated to the modified frobenius scalar
    """
    return np.sqrt(scalar(A,A))

def alphaaa1(S_2):
    """Pour une matrice de covariance non diagonale - cas de dependence
    arg = matrice q x q"""
    q = len(S_2)
    I_q = np.diag(np.ones(q))
    sigma2 = scalar(S_2,I_q)
    alpha2 = norm(S_2 - sigma2*I_q)**2
    return alpha2

def alphaaa2(vec):
    """Pour une matrice de covariance diagonale - cas de dependence
    arg = un vecteur qui represente la diagonale"""
    q = len(vec)
    I_q = np.diag(np.ones(q))
    S_2 = np.diag(vec)
    sigma2 = scalar(S_2,I_q)
    alpha2 = norm(S_2 - sigma2*I_q)**2
    return alpha2
```

```
[17]: ##### Preparing true covariance matrices for different
        ↪ values of q #####
```

```
valeur_propre_collection = [cov_toep(0.99,q) for q in q_list]
print(*valeur_propre_collection[q_list.index(50)][0][:10])
print([alphaaa1(cov_toep(0.99,q)) for q in q_list])
```

1.0 0.99 0.9801 0.970299 0.96059601 0.9509900498999999 0.941480149401
0.9320653479069899 0.9227446944279201 0.9135172474836408

```
[35.74129922798838, 55.63558896635379, 67.1216545130768, 74.1974025217765,
78.83310482926932, 82.04261087020382, 84.37246235469037, 86.13181245597147]
```

```
[18]: # list(product(n_list, range(K))[:12])
```

```
[19]: ##### Choosing dimension
↳#####

# K = int(input("Number of Monte Carlo iterations is : "))
print()
print("list of q values : ", q_list, "\n")
print("list of n values : ", n_list, "\n")

##### Generator function #####

def generator(n, q):
    """
    Creating a function that gets into paramaters :
        the number of observations
        the dimension
        dependency threshold
        2 covariance parameter
    and returns a matrix of n observations (n rows), where each row represents
    a q-vector normally distributed with a mean 0 and covariance matrix  $S^2$ 
    ↳defined
    by a toeplitz matrix with a threshold s
    """

    # defining eigenvalues, lognormal variables
    valeur_propre = valeur_propre_collection[q_list.index(q)]

    # defining a mean vector and a covariance matrix
    mean = np.zeros(q) ; cov = valeur_propre

    # z_intermediate = q rows and n columns we still need to transpose
    z_int = np.random.multivariate_normal(mean, cov, n).T

    # z sample matrix, having n rows and q columns
    z = np.transpose(z_int)

    # Returning the matrix of n-observations of dimension q
    return z

##### Statistics functions #####
```

```

def sn2(z):
    return np.cov(np.transpose(z))

def zbar(z):
    """takes a n x q sample matrix and return the vector mean of each column
    """
    return z.mean(axis=0)

def max_p(M):
    """Largest eigenvalue of a given matrix M"""
    val_p = np.linalg.eigvals(M)
    return max(val_p.real)

def min_p(M):
    """Smallest eigenvalue of a given matrix M that is not null"""
    val_p = np.linalg.eigvals(M)
    val_p = val_p[val_p>=10**-6]
    return min(val_p.real)

def product_vect(z, i):
    return np.matmul(z[i].reshape(z[i].shape[0], 1), np.transpose(z[i].
↳reshape(z[i].shape[0], 1)))

##### Algebra functions
↳#####

def scalar(A,B):
    """Takes two symmetric matrices A and B of sizes q
    and returns the modified frobenius scalar of A and B
    """
    return(np.trace(A.dot(np.transpose(B)))/A.shape[0])

def norm(A):
    """Takes a symmetric matrix A of sizes q
    and returns the norm of A
    This norm is associated to the modified frobenius scalar
    """
    return np.sqrt(scalar(A,A))

```

list of q values : [50, 100, 150, 200, 250, 300, 350, 400]

list of n values : [50, 75, 100, 125, 150, 175, 200]

1 Time comparison

```
[20]: def monte_carlo(k):
    # random.seed(k)
    np.random.seed(int(os.getpid() * time.time()) % 123456789)
    z = generator(n,q)
    sn_2 = sn2(z)
    # beta = (norm(sn_2 - s_2))**2
    # calculate empirical mean
    z_bar = zbar(z)
    #empirical covariance matrix
    sn_2 = sn2(z)

    # Calculating empirical eigenvalues and eigenvectors (of  $S_n^2$ )
    emp_val_p, emp_vec_p = np.linalg.eigh(sn_2)

    # Calculating true (theoretical) eigenvalues and eigenvectors (of  $S^2$ )
    # val_p, vec_p = np.linalg.eigh(s_2)

    # Identity matrix of size q
    I_q = np.diag(np.ones(q))

    # sigma_n ( ^ 2 )
    sigma_n = scalar(sn_2, I_q)

    # delta_n ( ^ 2 )
    delta_n = norm(sn_2 - sigma_n*I_q)**2

    # intermediate beta_n
    beta_bar_n = (1/n**2)*0
    for i in range(n):
        beta_bar_n += (1/n**2)*norm(product_vect(z, i) - sn_2)**2

    # beta_n ( ^ 2 )
    beta_n = min(beta_bar_n, delta_n)

    # alpha_n ( ^ 2 )
    alpha_n = delta_n - beta_n

    # rho_n ( * ^ 2 )
    rho_n = (beta_n/alpha_n)*sigma_n

    rho_1_n = (beta_n/delta_n)*sigma_n

    rho_2_n = alpha_n/delta_n

    Sigma_n_hat_ast = sn_2 + rho_n*I_q
```

```

Sigma_n_hat = rho_1_n*I_q + rho_2_n*sn_2

self_norm_sum = n*z_bar.dot(np.linalg.inv(Sigma_n_hat).dot(np.
↳transpose(z_bar)))
self_norm_sum_ast = n*z_bar.dot(np.linalg.inv(Sigma_n_hat_ast).dot(np.
↳transpose(z_bar)))
return np.array([self_norm_sum, self_norm_sum_ast, beta_n, sigma_n,
↳alpha_n, rho_n, max_p(sn_2),
min_p(sn_2)], dtype=np.int)

t1 = time.perf_counter()
dico = {}
for n in n_list[:3]:
    for q in q_list[:3]:
        if n <= q :
            dico[(n,q)] = np.stack(list(map(monte_carlo, range(10))))

print(dico[list(dico.keys())[0]])

t2 = time.perf_counter()

print(f'Finished in {t2-t1} seconds')

```

```

[[17 16  2  1 42  0 47  0]
 [32 30  0  0 11  0 24  0]
 [33 31  0  0 22  0 34  0]
 [36 34  1  0 20  0 32  0]
 [20 19  2  1 46  0 49  0]
 [12 11  1  0 29  0 40  0]
 [22 21  1  0 22  0 35  0]
 [24 23  2  1 45  0 49  0]
 [15 14  2  1 64  0 58  0]
 [24 23  1  0 27  0 37  0]]
Finished in 1.3481029690010473 seconds

```

```
[21]: len(dico.keys())
```

```
[21]: 7
```

```

[22]: t1 = time.perf_counter()
data = {}
for q in q_list[:3]:
    for n in n_list[:3]:
        if n <= q :
            with concurrent.futures.ProcessPoolExecutor() as executor:

```

```

        f1 = np.stack(list(executor.map(monte_carlo, range(10))))
        #f2 = f1.result()
        data[(n,q)] = f1
        # if q/n%1==0 : print(str(i)+","+str(j)+"",
                                #color.BLUE + color.BOLD + f"for n = %d \t",
↪and q = %d"%(n,q) + color.END, "\n",
                                #f1, "\n\n")

print(data[list(data.keys())[0]])

t2 = time.perf_counter()

print(f'Finished in {t2-t1} seconds')

```

```

[[23 22  1  0 26  0 37  0]
 [12 12  1  1 35  0 43  0]
 [19 18  2  1 61  0 57  0]
 [20 19  2  1 38  0 46  0]
 [ 9  8  3  1 58  0 55  0]
 [14 13  1  0 26  0 37  0]
 [16 15  1  0 24  0 36  0]
 [15 14  1  0 24  0 36  0]
 [11 11  2  1 45  0 49  0]
 [25 24  0  0 25  0 36  0]]
Finished in 1.5542298139989725 seconds

```

```
[23]: data[list(data.keys())[1]]
```

```
[23]: array([[36, 34,  1,  0, 34,  0, 58,  0],
            [40, 38,  2,  1, 55,  0, 75,  0],
            [31, 29,  2,  0, 37,  0, 62,  0],
            [45, 43,  1,  0, 24,  0, 46,  0],
            [49, 47,  2,  1, 62,  0, 80,  0],
            [46, 43,  3,  0, 50,  0, 73,  0],
            [36, 33,  2,  0, 33,  0, 58,  0],
            [39, 37,  3,  1, 65,  0, 81,  0],
            [57, 54,  4,  1, 95,  0, 99,  0],
            [35, 32,  1,  0, 19,  0, 43,  0]])
```

2 Generating step

```
[24]: K = int(input("Number of Monte Carlo iterations is : "))
```

```
Number of Monte Carlo iterations is : 999
```



```
[25]: t_init = time.perf_counter()
dico = {}
for n in n_list:
    for q in q_list:
        t1 = time.perf_counter()
        if n <= q :
            dico[(n,q)] = np.stack(list(map(monte_carlo, range(10))))
            t2 = time.perf_counter()
            if q==n or q==2*n :
                print(f"q = {q} and n = {n} --> ",f'Finished in {round(t2-t1,4)} seconds')

print(dico[list(dico.keys())[0]][0][:10])

t_fin = time.perf_counter()
print()
print(f'All loops finished in {round(t_fin-t_init, 3)} seconds')
```

```
q = 50 and n = 50 --> Finished in 0.0503 seconds
q = 100 and n = 50 --> Finished in 0.0863 seconds
q = 150 and n = 75 --> Finished in 0.2668 seconds
q = 100 and n = 100 --> Finished in 0.1252 seconds
q = 200 and n = 100 --> Finished in 0.5247 seconds
q = 250 and n = 125 --> Finished in 1.1458 seconds
q = 150 and n = 150 --> Finished in 0.4823 seconds
q = 300 and n = 150 --> Finished in 2.7629 seconds
q = 350 and n = 175 --> Finished in 3.5474 seconds
q = 200 and n = 200 --> Finished in 1.0641 seconds
q = 400 and n = 200 --> Finished in 5.6463 seconds
[[12 11 2 1 39 0 46 0]
 [23 23 0 0 25 0 36 0]
 [25 24 1 0 31 0 41 0]
 [23 22 1 0 20 0 33 0]
 [16 15 2 1 47 0 50 0]
 [31 30 1 0 33 0 42 0]
 [10 9 1 0 23 0 36 0]
 [13 12 1 0 30 0 40 0]
 [19 18 2 1 38 0 45 0]
 [16 15 0 0 14 0 27 0]]
```

All loops finished in 77.982 seconds

```
[26]: def monte_carlo(k):
    # random.seed(k)
    np.random.seed(int(os.getpid() * time.time()) % 123456789)
    z = generator(n,q)
    sn_2 = sn2(z)
```

```

s_2 = valeur_propre_collection[q_list.index(q)]
beta = (norm(sn_2 - s_2))**2
# calculate empirical mean
z_bar = zbar(z)
#empirical covariance matrix
sn_2 = sn2(z)

# Calculating empirical eigenvalues and eigenvectors (of  $S_n^2$ )
emp_val_p, emp_vec_p = np.linalg.eigh(sn_2)

# Calculating true (theoretical) eigenvalues and eigenvectors (of  $S^2$ )
# val_p, vec_p = np.linalg.eigh(s_2)

# Identity matrix of size q
I_q = np.diag(np.ones(q))

# sigma_n ( ^2 )
sigma_n = scalar(sn_2, I_q)

# delta_n ( ^2 )
delta_n = norm(sn_2 - sigma_n*I_q)**2

# intermediate beta_n
beta_bar_n = (1/n**2)*0
for i in range(n):
    beta_bar_n += (1/n**2)*norm(product_vect(z, i) - sn_2)**2

# beta_n ( ^2 )
beta_n = min(beta_bar_n, delta_n)

# alpha_n ( ^2 )
alpha_n = delta_n - beta_n

# rho_n ( *^2 )
rho_n = (beta_n/alpha_n)*sigma_n

rho_1_n = (beta_n/delta_n)*sigma_n

rho_2_n = alpha_n/delta_n

Sigma_n_hat_ast = sn_2 + rho_n*I_q
Sigma_n_hat = rho_1_n*I_q + rho_2_n*sn_2

self_norm_sum = n*z_bar.dot(np.linalg.inv(Sigma_n_hat).dot(np.
↪transpose(z_bar)))
self_norm_sum_ast = n*z_bar.dot(np.linalg.inv(Sigma_n_hat_ast).dot(np.
↪transpose(z_bar)))

```

```

    return np.array([self_norm_sum, self_norm_sum_ast, beta_n, sigma_n,
↳alpha_n, rho_n, max_p(sn_2),
                    min_p(sn_2), beta])

```

```

[27]: print(color.BLUE + color.BOLD + '***** Starting the extraction !'
↳*****' + color.END )

K = int(input("Number of Monte Carlo iterations is : "))
t_init = time.perf_counter()
dico = {}
for n in n_list:
    for q in q_list:
        t1 = time.perf_counter()
        if n <= q :
            dico[(n,q)] = np.stack(list(map(monte_carlo, range(K))))
            t2 = time.perf_counter()
            if q==n or q==2*n :
                print(f"q = {q} and n = {n} --> ",f'Finished in {round(t2-t1,
↳4)} seconds')

print(dico[list(dico.keys())[0]][0][:10])

t_fin = time.perf_counter()
print()
print(f'All loops finished in {round(t_fin-t_init, 3)} seconds')

```

***** Starting the extraction ! *****

```

Number of Monte Carlo iterations is : 999
q = 50 and n = 50 --> Finished in 3.7521 seconds
q = 100 and n = 50 --> Finished in 8.4912 seconds
q = 150 and n = 75 --> Finished in 28.0677 seconds
q = 100 and n = 100 --> Finished in 30.1414 seconds
q = 200 and n = 100 --> Finished in 130.4157 seconds
q = 250 and n = 125 --> Finished in 217.6728 seconds
q = 150 and n = 150 --> Finished in 71.7104 seconds
q = 300 and n = 150 --> Finished in 376.5496 seconds
q = 350 and n = 175 --> Finished in 594.7796 seconds
q = 200 and n = 200 --> Finished in 180.3045 seconds
q = 400 and n = 200 --> Finished in 1054.9941 seconds
[[3.21952376e+01 3.10150524e+01 7.11801162e-01 7.74766911e-01
 1.87060062e+01 2.94814394e-02 3.13576569e+01 1.04305480e-05
 2.66646422e+00]
 [1.58018970e+01 1.50726312e+01 1.55567635e+00 9.63912677e-01
 3.21530736e+01 4.66374125e-02 4.14331898e+01 1.23171019e-05
 4.33843232e-01]
 [2.38948749e+01 2.26396453e+01 1.24945839e+00 8.43273886e-01
 2.25355540e+01 4.67543699e-02 3.47204240e+01 1.91892136e-06

```

```

1.45305188e+00]
[1.48164040e+01 1.38989302e+01 3.62768241e+00 1.22649215e+00
5.49562317e+01 8.09612282e-02 5.46689243e+01 7.49985260e-06
3.30060712e+00]
[1.40688199e+01 1.30875111e+01 5.01252764e+00 1.38977875e+00
6.68510356e+01 1.04206380e-01 6.04238849e+01 5.24114757e-05
6.98224785e+00]
[2.14795707e+01 2.05093405e+01 2.47552942e+00 1.19821392e+00
5.23293052e+01 5.66836078e-02 5.28495461e+01 7.34089613e-06
2.28001743e+00]
[1.74796520e+01 1.68958670e+01 1.11538497e+00 9.74024052e-01
3.22814009e+01 3.36544190e-02 4.11613570e+01 4.31547260e-06
6.55340018e-01]
[1.73714222e+01 1.66508228e+01 1.33758807e+00 9.78928856e-01
3.09075196e+01 4.23652101e-02 4.04156895e+01 9.64826294e-06
6.69483702e-01]
[2.63460685e+01 2.49666493e+01 1.72078569e+00 9.39745335e-01
3.11451747e+01 5.19213759e-02 4.09484789e+01 1.03666823e-05
1.99555910e-01]
[3.21045671e+01 3.05140447e+01 2.70927656e+00 1.20189590e+00
5.19772522e+01 6.26479519e-02 5.27637989e+01 1.44505065e-05
2.22342701e+00]]

```

All loops finished in 12819.036 seconds

```
[28]: pickle.dump(dico, open("data_d_s0.99", "wb"))
```

```
[29]: teeest = pickle.load(open("data_d_s0.99", "rb"))
len(teeest[list(teeest.keys())[0]][:,:])
```

```
[29]: 999
```

```
[30]: print(teeest[list(teeest.keys())[0]][:,:])
```

```

[32.19523757 15.80189695 23.89487488 14.81640401 14.06881987 21.47957073
17.47965199 17.37142225 26.34606849 32.10456712 18.90710812 35.21434059
16.41328806 18.70887049 26.99265713 25.4879795 27.45100905 18.65066424
20.04724445 17.95743187 12.70408048 27.96108477 37.59509942 29.13596961
32.80142467 20.31098177 38.14106264 18.16441563 25.29244995 22.93025313
20.70963424 17.91635523 20.71352662 14.98602769 19.55511269 26.57521169
29.54276634 16.3618215 36.7957392 31.12048128 21.58148172 17.45545827
18.44907662 28.34065285 19.09601013 16.71445689 14.318893 18.21714379
10.24198793 30.07984393 36.61293907 15.84908024 12.40630342 14.21289174
24.68740781 17.59144989 24.31415299 13.22510019 18.81581884 36.5785202
16.41400052 14.28758412 9.55724017 28.57306457 20.71965413 18.24806039
24.42370481 28.95239037 23.00849872 20.42853623 14.27368697 9.97168807
20.06070935 16.55865031 25.3904365 17.80131985 9.34655483 18.0944154
21.99211982 12.05998174 17.51636642 28.77100146 16.23402093 27.30643612

```

15.16221753 24.58433238 24.53671158 22.08373828 16.34617536 18.28717495
19.97954536 12.25860582 32.31104936 11.96916653 13.58592018 20.72554146
13.46930618 21.81002787 25.78203811 26.50447317 30.59474952 44.95519194
14.09714471 24.78587802 19.29329001 13.14365089 15.9773684 15.25759351
21.03730467 11.08534256 11.56063534 25.58498073 24.63642576 32.65976871
18.66434821 16.62865518 18.01302295 21.21631731 15.70765423 17.17877074
26.84019579 16.48285308 24.35000913 21.46558245 7.74558607 17.54680568
22.14067614 20.22379356 16.17508331 15.63574384 27.06920418 26.01939326
12.18189573 28.21009437 31.08350156 22.56461371 21.39959698 14.05110296
12.38472658 13.55983531 14.94223725 19.57064303 16.2921108 27.56572954
21.20914937 15.41160369 18.10213129 26.58358335 28.20631465 17.57277008
13.41243238 24.03662873 21.0269898 18.19623509 24.49952284 22.98200912
31.53124624 20.28912817 27.96059447 18.70498148 22.27786549 30.82603081
24.13881961 22.47105248 28.23628547 12.74203473 17.88253028 14.52211938
21.47429562 43.21531755 22.83275824 18.85683271 12.0963194 18.80422742
17.16823709 18.69559487 10.28063417 13.36757335 20.27443267 19.38327505
14.17610973 22.5320225 17.90599958 25.74824091 19.98611758 35.36280504
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