

MASTER'S DEGREE IN PHYSICS
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QUANTUM INFORMATION

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EXERCISE 5

In this report I am going to review how I solved problems 1 and 2 of Ex. 5, using Fortran functions and subroutines and Gnuplot scripts.

Theory

Mathematically, a Hermitian matrix is a matrix which is equal to its transpose conjugate. The Spectral theorem for finite dimension says that any hermitian matrix can be diagonalized by a unitary matrix; this implies that all eigenvalues of a Hermitian matrix A with dimension n are real, and that A has n independent eigenvectors.

$$H = \begin{bmatrix} 2 & 2+i & 4 \\ 2-i & 3 & i \\ 4 & -i & 1 \end{bmatrix}$$

This, in particular, shows us the equivalence of Hermitian matrices to real diagonal matrices. We are going to use this fact to compare the distribution of distances of contiguous eigenvalues in Hermitian and real diagonal matrices in order to see if they are the same.

Code Development

For this exercise I divided my code in two blocks, one for each problem: `Eigenproblem.f90` and `Statistics.f90`. The purpose of `Eigenproblem.f90` is to solve problem 1 generate a dataset for problem 2.

Problem 1 asked to consider an Hermitian matrix, so I chose as fundamental type of my problem the structure `type(dmatriX)` used in previous assignments:

```
1 type dmatriX
2   integer, dimension(2) :: N = (/ 0,0 /)
3   double complex, dimension(:, ::), allocatable :: elem
4   double complex, dimension(:, ::), allocatable :: evec
5   double precision, dimension(:), allocatable :: eval
6   double complex :: Trace
7   double complex :: Det
8 end type dmatriX
```

The procedure to follow in order to create a meaningful dataset for problem two is the following:

1. Matrix initialization
2. matrix diagonalization
3. normalized spacings calculation
4. output to file
5. repeat

Writing this code I wanted to assign as many operation as possible to functions, in order to be able to automatize them efficiently; I also used as many LAPACK functions as I could in order to call the best implementation possible for the various algorithms.

For the first step of the algorithm I implemented `function InitHerm(herm_1, Nmat)`: this function takes as input a `type(dmatriX)` object and initializes it to a Hermitian matrix of size `Nmat`. In particular, all

array fields of the structure are allocated, all scalars are initialized to 0 and the `double complex` array containing the matrix is initialized to a random Hermitian matrix using the LAPACK subroutine `zlaghe`.

The second step of the algorithm is performed in a similar way, using

```
1 function DmatHermEv(herm_1)
```

which is nothing else than a simple interface between the LAPACK solver `zheev` and the custom `type` (`dmatrix`). I used in this program to manage complex matrices; as a matter of fact, `herm_1` is a `type` (`dmatrix`) data. The eigenvalues of the input matrix are stored in a crescent order in the `herm_1%eval` field of the output.

The last strictly computational step regards computation of normalized spacings between eigenvalues. I included this operation into

```
1 function SpAvg(herm_1).
```

I computed normalized spacings using the `eoshift` intrinsic function, which shifts all the elements of an array of an arbitrary amount along a specified direction. Subtracting a properly shifted array to the one containing the original eigenvalues gives the spacings S_i , as shown in the code below:

```
1 function SpAvg(herm_1)
2   implicit none
3   ! Local custom types
4   type(dmatrix) :: herm_1
5   ! Local scalars
6   integer :: Nmat, sp_size
7   double precision :: s_avg, sp_sum
8   ! Local arrays
9   double precision, dimension(:), allocatable :: values, sp_0, sp
10  double precision, dimension(herm_1%N(1)-1) :: SpAvg
11
12  allocate(values(herm_1%N(1)))
13  allocate(sp_0(herm_1%N(1)))
14  allocate(sp(size(sp_0)-1))
15  values = herm_1%eval
16  sp_0=values
17  values=eoshift(values, shift=-1)
18  sp_0 = sp_0-values
19  sp=sp_0(2:)
20  sp_size = size(sp)
21  sp_sum = sum(sp)
22  s_avg = sp_sum/sp_size
23  sp=sp(:)/s_avg
24
25  SpAvg = sp
26 end function SpAvg
```

I chose to use this method because it allows not read explicitly all the eigenvalues with a loop in order to compute S_i .

Output and repetition are implemented in the main file `Eigenproblem.f90` itself. This program is essentially a loop that repeats initialization, diagonalization and output for a fixed matrix size (`Nmat`) `Ncycles` times. This program produces a dataset automatically named after the matrix size and the number of iterations (e.g. `Sp_1000_0100.dat`) which contains in each row all the normalized spacings between the eigenvalues of an hermitian matrix for a `Ncycles` number of rows. A live output of the percentage of completion of the loop is displayed on screen.

The code is the following:

```
1 ! External modules:
2 include "ModDmat.f90"
3 include "ModDebug.f90"
4
5 program Eigenproblem
6   use ModDmat
7   use ModDebug
8   implicit none
9   ! Local scalars
10  integer :: Nmat, Nsp, ios, ii,jj, Ncycles
11  character(len=100) :: filename, msg, x1,x2, format
12  ! Local arrays
13  double precision, dimension(:), allocatable :: spacings
```

```

14  double precision :: perc, start, end, time
15  ! Local custom types
16  type(dmatrix) :: herm_1
17
18  Nmat = 1000
19  Ncycles=100
20  ... Initialization of filename and some parameters ...
21  do jj=1,Ncycles
22      call cpu_time(start)
23      allocate(herm_1%elem(Nmat,Nmat))
24      herm_1=herm_1 .Init. Nmat
25      herm_1 =.evalh. herm_1
26      if (isnan(sum(herm_1%eval))) go to 129
27      spacings=SpAvg(herm_1)
28
29      write(x1,'(i4.4)') Nmat
30      do ii=1,Nsp
31          write(55,'(g13.6)', advance='no') spacings(ii)
32      end do
33      129 deallocate(herm_1%elem)
34      deallocate(herm_1%eval)
35      write(55,*)
36      call cpu_time(end)
37      time=end-start
38      perc=100*jj/Ncycles
39      write(*, "('Elapsed time [s]: ',(G9.2),(G9.2),' % done...')' ) time, floor(perc)
40  end do
41  close(55)
42 end program Eigenproblem

```

The solution of problem 2 is computed by the program Statistics.f90 by using the output files from Eigenproblem.f90. To make some statistics on the data I chose to define a `type(histogram)` structure. I created this place to store in a compact and ordered way the histograms and all the related informations that I needed for the analysis, but I couldn't fit into a single array:

```

1  type histogram
2      integer :: Nbins, entries
3      double precision :: lower, upper
4      integer, dimension(:), allocatable :: h
5      double precision, dimension(:), allocatable :: hnorm
6      double precision, dimension(:), allocatable :: bounds, bincenters
7  end type histogram

```

Statistics.f90 basically works on two of these histograms: it loads the data, it fills them and it saves the relevant information onto an automatically named file like Eigenproblem.f90 did. The first one, `h1`, contains the data retrieved from diagonalization of random Hermitian matrices, while the second one, `h2`, contains data from randomly generated double precision diagonal matrices. The generation of random double precision data is made with the intrinsic subroutine `random_number`; this data is then sorted in a crescent order using LAPACK subroutine `dasrt` and passed to a appropriately modified `SpAvg` function (`SpAvgDble`) that returns the normalized spacings.

```

1  ! External modules:
2  include "ModDmat.f90"
3  include "ModDebug.f90"
4
5  program Statistics
6      use ModDmat
7      use ModDebug
8      implicit none
9      ! Local scalars
10     character(len=100) :: msg, x1, x2, filename, filename_1
11     integer :: Nsp, Ncy, ios, Nbins, ii, seme_dim=4
12     double precision :: h_lenght, h_step, h_lower, h_upper
13     ! Local arrays
14     double precision, dimension(:,:), allocatable :: indata
15     double precision, dimension(:), allocatable :: diag_rnd, sp_diag
16     double precision, dimension(:), allocatable :: h_bounds, h_input_aux
17     integer, dimension(:), allocatable :: h_input, h, seme
18
19     ! Local custom types
20     type(histogram) :: h1, h2
21     ... filename definition ...

```

```

22  Nsp=1999
23  Ncy=450
24  h_lower = 0
25  h_upper = 8
26  Nbins=50
27
28  allocate(indata(Ncy,Nsp),diag_rnd(Nsp+1),sp_diag(Nsp))
29  indata = LoadArray("Sp_2000_0450.dat",Ncy,Nsp)
30
31  h1=InitHisto(h_lower,h_upper,Nbins)
32  h2=InitHisto(h_lower,h_upper,Nbins)
33  do ii=1,Ncy
34      call FillH(h1,indata(ii,:), "y")
35  end do
36
37  call random_seed()
38  call random_seed(size=seme_dim)
39  allocate(seme(seme_dim))
40  call random_seed(get=seme)
41  call random_number(diag_rnd)
42
43  call dlasrt('I',Nsp+1,diag_rnd,ios)
44  sp_diag=SpAvgDble(diag_rnd)
45
46  call FillH(h2,sp_diag, 'y')
47
48  call HistoToFile(h1,filename)
49  call HistoToFile(h2,filename_1)
50
51 end program Statistics

```

Histograms are filled by `subroutine FillH(h1,indata,norm)`. This function uses an `intent(inout)` argument `type(histogram) :: h` (previously initialized by a specific function), an argument for input data `indata` and a flag that specifies if a normalized histogram has to be saved or not `norm`. Using `FillH`, `indata` is sort into `h%Nbins` categories comprised into bounds defined in `h%bounds` vector; a vector with the center of the bins is also saved for plotting purposes.

```

1  subroutine FillH(h1,indata,norm)
2      implicit none
3      ! Local scalars
4      integer :: Nentries
5      double precision :: step
6      character(*),intent(in) :: norm
7      ! Local arrays
8      double precision, dimension(:), intent(in) :: indata
9      double precision, dimension(:), allocatable :: h_input_aux
10     integer, dimension(:), allocatable :: h_input
11
12     ! Local custom types
13     type(histogram),intent(inout) :: h1
14
15     step = (h1%upper - h1%lower)/h1%Nbins
16     Nentries=size(indata)
17     allocate(h_input_aux(Nentries),h_input(Nentries))
18     h_input_aux= indata
19     h_input_aux = ceiling(h_input_aux/step)
20     h_input=int(h_input_aux)
21     h1%h(h_input) = h1%h(h_input)+1
22     h1%entries = sum(h1%h)
23     if(norm=="y".and. h1%entries/=0) then
24         h1%hnorm=dbl(h1%h)/h1%entries*step
25     end if
26 end subroutine FillH

```

In the end, `Statistics.f90` gives as output a text file for each histogram, containing center coordinates and normalized values for each bin.

Results and self evaluation

To retrieve the fit parameters requested by problem 2, I chose to generate a dataset of normalized eigenvalue spacings retrieved from 2000×2000 matrices; I set the `Eigenproblem.f90` cycles counter to

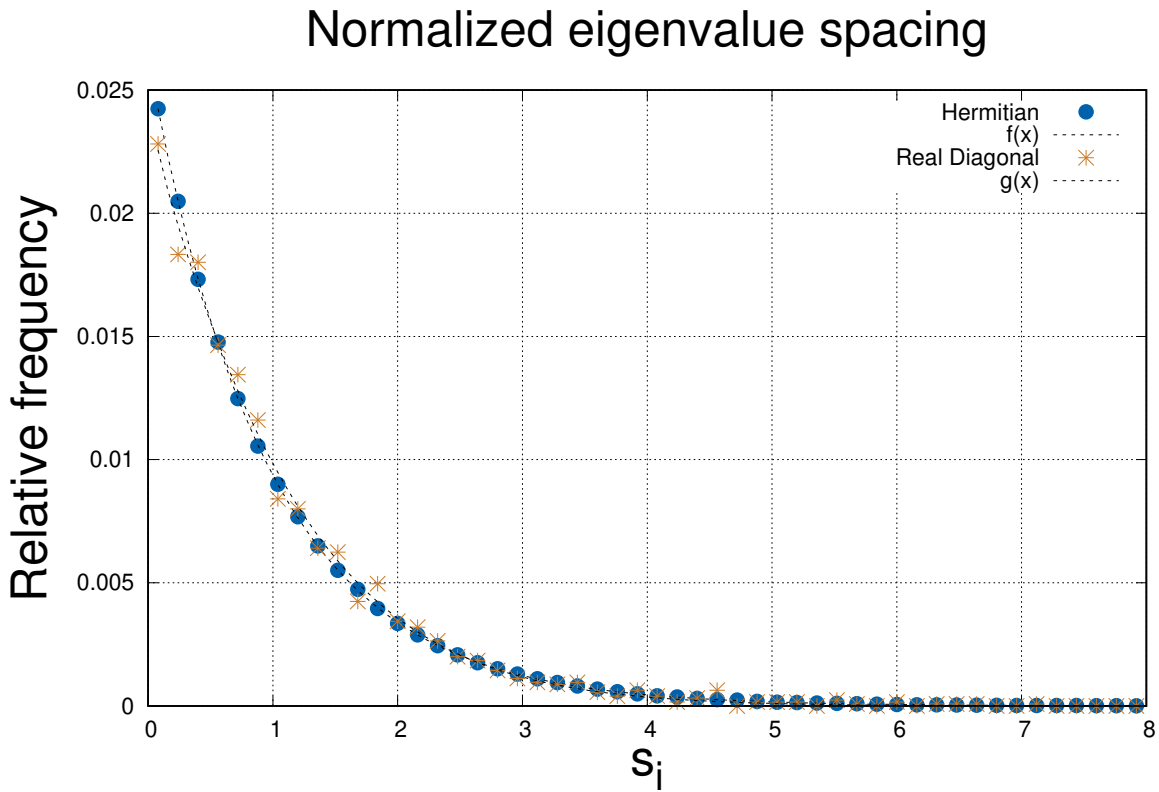


Figure 1: Normalized eigenvalue spacings from random Hermitian matrices (blue) and from random real diagonal matrices (orange).

450 to generate approximately 9×10^5 data points (normalized spacings). I filled an histogram with these data, which can be seen in figure 1. For both histograms I set $Nbins = 50$ and a binning interval spanning from 0 to 8 (dimensionless); this produces little dispersion of data, of the order of 10^2 points, which is negligible.

The data retrieved from Fortran programs as described above has been fitted to the law

$$f(x) = ax^\alpha \exp(bx^\beta)$$

using gnuplot. Results for a, α, b, β are the following for the two datasets:

Table 1: Fit results for Hermitian (first row) and real diagonal (second row) matrices.

	a	α	b	β	$\chi^2/\text{d.o.f.}$
$f(x)$	0.0263 ± 0.0002	-0.001 ± 0.003	1.033 ± 0.008	0.987 ± 0.002	1.6×10^{-8}
$g(x)$	0.021 ± 0.002	-0.04 ± 0.04	0.8 ± 0.1	$1.2 \pm 0.1 \pm 0.005$	3×10^{-4}

As a conclusion we can observe that some parameters of the two distributions are not compatible and therefore we cannot state that they are the same. Nonetheless the similarity between the two is remarkable and it is a clear sign of correlation, which might be confirmed by more specific analysis.