Problem 3.e) The following code is used for calculating $S(t) = \exp(At)$ using the Python package **linalg**.

```
#!/usr/bin/env python3
#_-*- coding: utf-8 -*-
Created on Thu Oct 18 11:26:04 2018
@author: alfred_mac
import numpy as np
import scipy.linalg as sla
import matplotlib.pyplot as plt
N = 100
A = np.array([[0,1],[-1,0]])
t = np. linspace (0,7,N)
S11 = np.zeros(N)
S12 = np.zeros(N)
S21 = np.zeros(N)
S22 = np.zeros(N)
E = sla.eig(A)
                         # Eigen values and eigen vectors of A
R = E[1]
                         \# R = eigen vectors of A
L = sla.inv(R)
                         \# L = inv(R)
e = E[0]
                         # Eigen values of A
for i in range (N):
    \exp_e = \operatorname{np.diag}(\operatorname{np.exp}(t[i]*e)) # Exponent of tA
    S = np.matmul(R, np.matmul(exp_e, L)) \# Calculating S(t)
    # Taking only the real parts as the imaginary parts are insignificant
    S11[i] = np.real(S[0][0])
    S12[i] = np.real(S[0][1])
    S21[i] = np.real(S[1][0])
    S22[i] = np.real(S[1][1])
plt.plot(t,S11, 'r o')
plt . plot (t, S12)
```

```
\begin{array}{l} {\rm plt.\,plot}\,(t\,,S21) \\ {\rm plt.\,plot}\,(t\,,S22\,,~'g--') \\ {\rm plt.\,legend}\,([\,'\$S_{\{11\}}(t)\$\,'\,,'\$S_{\{12\}}(t)\$\,'\,,'\$S_{\{21\}}(t)\$\,'\,,'\$S_{\{22\}}(t)\$\,']) \\ {\rm plt.\,xlabel}\,(\,'t\,') \\ {\rm plt.\,ylabel}\,(\,'\$S_{\{ij\}}(t)\$\,') \\ {\rm plt.\,show}\,() \end{array}
```

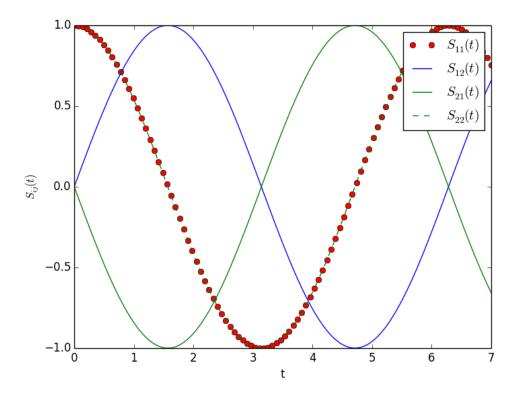


Figure 1: $S_{ij}(t)$ vs t using Python package **linalg**

Problem 4) The following code is used for calculating S(t) = exp(At) by computing the Taylor series using Horner's rule.

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
Created on Thu Oct 18 19:50:33 2018
@author: alfred_mac
"""
```

```
import numpy as np
import matplotlib.pyplot as plt
# Function definition applying Horner's rule to calculate the series
def expm_alf(t,M,k):
    S = np.eye(len(M)) + (t/k)*M
    for i in range (k-1):
        S = np. eye(len(M)) + (t/(k-1-i))*np.matmul(M,S)
    return S
# Function to convert a positive integer to a string of digits in base 2 (Source
def N_to_base2(n):
    if n == 0:
        return [0]
    digits = []
    while n:
        digits.append(int(n\%2))
        n //= 2
    return digits [::-1]
# Function to calculate 2's powers of any matrix to be used for any power of a n
def Bs_for_N_to_base2(B,n):
    if n == 0:
        return np.eye(len(B))
    Blist = []
    while n:
        Blist.append(B)
        B = np.matmul(B,B)
        n //= 2
    return Blist [::-1]
# Function calculating any power of a matrix
def B_pow_n(B, digits):
    S = np.eye(2)
    for i in range(len(digits)):
        if digits[i]==1:
            S = np.matmul(S,B[i])
    return S
T = 7
                                 # Total simulation time
deltat = 0.1
                                 # delta t used for time step
N = int(T/deltat)
                                # Total no. of time steps
A = np. array([[0,1],[-1,0]])
                              # given A
```

```
S11 = np.zeros(N)
S12 = np.zeros(N)
S21 = np.zeros(N)
S22 = np.zeros(N)
k=1
S1 = np.eye(2)
S2 = \exp m_a \operatorname{alf} (\operatorname{deltat}, A, k)
# Loop to find which k to use to achieve the required level of accuracy
while (np. max (abs (S1-S2)) > 1e-10):
    \mathbf{k} \ = \ \mathbf{k}{+}\mathbf{1}
    S1 = S2
    S2 = \exp m_a \operatorname{alf} (\operatorname{deltat}, A, k)
for i in range(N):
    i_base2 = N_to_base2(i)
    Sti = B_pow_n(Bs_for_N_to_base2(S2,i), N_to_base2(i))
    # Taking only the real parts as the imaginary parts are insignificant
    S11[i] = np.real(Sti[0][0])
    S12[i] = np.real(Sti[0][1])
    S21[i] = np.real(Sti[1][0])
    S22[i] = np.real(Sti[1][1])
t = np. arange(0, T, deltat)
plt.plot(t,S11, 'r o')
plt . plot (t, S12)
plt . plot (t, S21)
plt.plot(t,S22, 'g--')
plt.xlabel('t')
plt.ylabel('$S_{ij}(t)$')
plt.show()
  The following code is used for computing B^n just using O(log(n)) matrix
multiplications.
#!/usr/bin/env python3
\# -*- coding: utf-8 -*-
Created on Thu Oct 18 19:50:33 2018
```

```
@author: alfred_mac
import numpy as np
# Function definition applying Horner's rule to calculate the series
def expm_alf(t,M,k):
    S = np.eye(len(M)) + (t/k)*M
    for i in range (k-1):
         S = np.eye(len(M)) + (t/(k-1-i))*np.matmul(M,S)
    return S
deltat = 0.2
                                     # delta t used for time step
A = np.array([[0,1],[-1,0]])
                                  # given A
k=1
S1 = np.eye(2)
S2 = \exp m_a \operatorname{alf} (\operatorname{deltat}, A, k)
# Loop to find which k to use to achieve the required level of accuracy
while (np. max (abs (S1-S2)) > 1e-10):
     print ("When k is", k, 'error is ', np.max(abs(S1-S2)))
    k = k+1
    S1 = S2
    S2 = \exp m_a \operatorname{alf} (\operatorname{deltat}, A, k)
print ("Finally when k is", k, 'error is ', np.max(abs(S1-S2)))
print ("S is ",S2)
  Problem 5) The following is the code to solve the system of differential
equations using the eigen value method
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
Created on Thu Oct 25 15:20:58 2018
@author: alfred_mac
,, ,, ,,
import numpy as np
import scipy.linalg as sla
import matplotlib.pyplot as plt
```

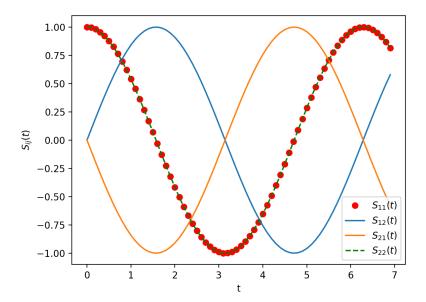


Figure 2: $S_{ij}(t)$ vs t by computing Taylor's series using Horner's rule

```
N = 100
                        # Time length of the simulation
n = 50
                        # Total no. of spots (or the size of X vector)
A = np.zeros([n,n])
                        # Matrix defining the dynamics
p = 0.7
                        # Rate at which particles move left
q = 0.3
                        # Rate at which particles move right
# Defining the matrix A
A[0,0] = -p
A[0,1] = p
A[n-1,n-2] = q
A[n-1,n-1] = -q
for i in range (n-2):
    A[i+1,i] = q
    A[i+1,i+1] = -(p+q)
    A[i+1,i+2] = p
```

t = np. linspace(0,7,N) # Time counter

```
X = np.zeros([n,N])
                          # No. of particles at different spots at different times
X[0,0] = 1
                          # Initial condition for no. of particles, X
                          # Eigen values and eigen vectors of A
E = sla.eig(A)
R = E[1]
                          \# R = eigen vectors of A
L = sla.inv(R)
                          \# L = inv(R)
e = np.real(E[0])
                          # Eigen values of A
AA = np.eve(n)
for i in range (N-1):
    \exp_e = \operatorname{np.diag}(\operatorname{np.exp}(t[i]*e))
                                           # Exponent of tA
     AA = np. eye(n) + np. matmul(AA, A)
    S = np.matmul(R,np.matmul(exp_e,L)) # Calculating S(t)
    X[:, i+1] = np.matmul(S, X[:, 0])
     X[:, i+1] = np.matmul(AA, X[:, 0])
plt.plot(t, X[0,:], ro')
plt.legend(['$x_{-}{1}(t)$'])
plt.xlabel('t')
plt.ylabel('$x_{-}{1}(t)$')
plt.show()
  Problem 6) The following code is to compute the matrix product AB when
A and B are n \times n matrices
#!/usr/bin/env python3
\# -*- coding: utf-8 -*-
Created on Thu Oct 25 15:42:44 2018
@author: alfred_mac
import numpy as np
import random as rnd
import numpy.random as nprnd
import time as t
import matplotlib.pyplot as plt
def matprod_scalar_loop(P,Q):
    if len(P.T) = len(Q):
        R = np. zeros([len(P), len(Q.T)])
         for i in range (len(P)):
             for j in range (len (Q.T)):
```

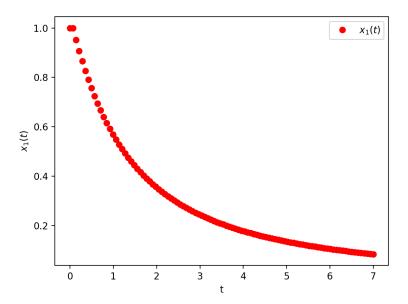


Figure 3: No. of particles at spot 1 over time, $x_1(t)$ vs t

```
for k in range (len(Q)):
                    R[i][j] += P[i][k]*Q[k][j]
    elif len(Q.T) = len(P):
        R = np.zeros([len(Q), len(P.T)])
        for i in range (len (Q)):
            for j in range(len(P.T)):
                 for k in range(len(P)):
                    R[i][j] += Q[i][k]*P[k][j]
    else:
        print ("Can't multiply theses matrices :(")
        return
    return R
def matprod\_vector\_loop(P,Q):
    if len(P.T) = len(Q):
        R = np.zeros([len(P), len(Q.T)])
        for i in range(len(P)):
```

```
for j in range(len(Q.T)):
                R[i][j] = np.sum(P[i,:]*Q[:,j])
    elif len(Q.T) = len(P):
        R = np.zeros([len(Q), len(P.T)])
        for i in range (len(Q)):
            for j in range(len(P.T)):
                R[i][j] = np.sum(Q[i,:]*P[:,j])
    else:
        print ("Can't multiply theses matrices :(")
    return R
def matprod_numpy(P,Q):
    return np.matmul(P,Q)
nstart = 10
nend = 300
nstep = 10
N = np.arange(nstart, nend+1, nstep)
T1 = np.zeros(len(N))
T2 = np.zeros(len(N))
T3 = np.zeros(len(N))
for n in range (len(N)):
    A = nprnd.rand(N[n],N[n])
    B = nprnd.rand(N[n],N[n])
    t0 = t.time()
    C = matprod_scalar_loop(A,B)
    t1 = t.time()
    D = matprod_vector_loop(A,B)
    t2 = t.time()
    E = matprod_numpy(A,B)
    t3 = t.time()
    T1[n] = t1-t0
    T2[n] = t2-t1
    T3[n] = t3-t2
plt.plot(N,T1)
plt.plot(N,T2)
```

```
\begin{array}{l} plt.\,plot\,(N,T3)\\ plt.\,legend\,(\,[\,'T1\,'\,,\,'T2\,'\,,\,'T3\,'\,]\,)\\ plt.\,xlabel\,(\,'N\,'\,)\\ plt.\,ylabel\,(\,'Time\ taken\,'\,)\\ plt.\,show\,(\,) \end{array}
```

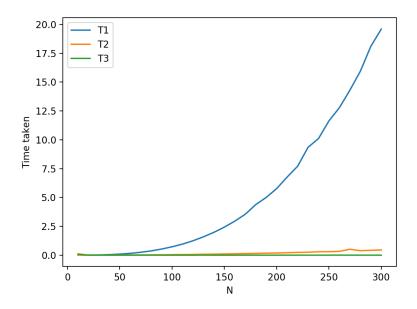


Figure 4: Time taken for computing matrix products as a function of the size of the matrix, n