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Math 6680  
HW 2

5.1. Modify Program 9 to compute and plot the maximum error over  $[-1, 1]$  for equispaced and Chebyshev interpolation on a log scale as a function of  $N$ . What asymptotic divergence and convergence constants do you observe for these two cases? (Confine your attention to small enough values of  $N$  that rounding errors are not dominant.) Now, based on the potential theory of this chapter, determine exactly what these geometric constants should be. How closely do your numerical experiments match the theoretical answers? <sup>1</sup>

Here, we are choosing  $N$  to be multiples of 4 between 4 and 28.

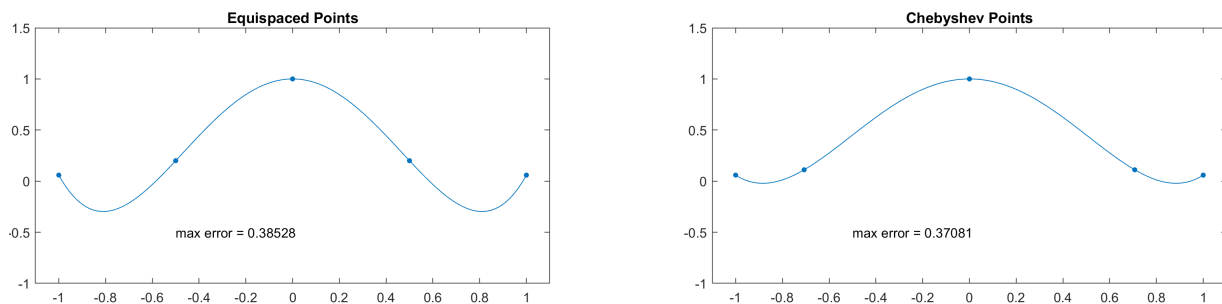


Figure 1:  $N = 4$

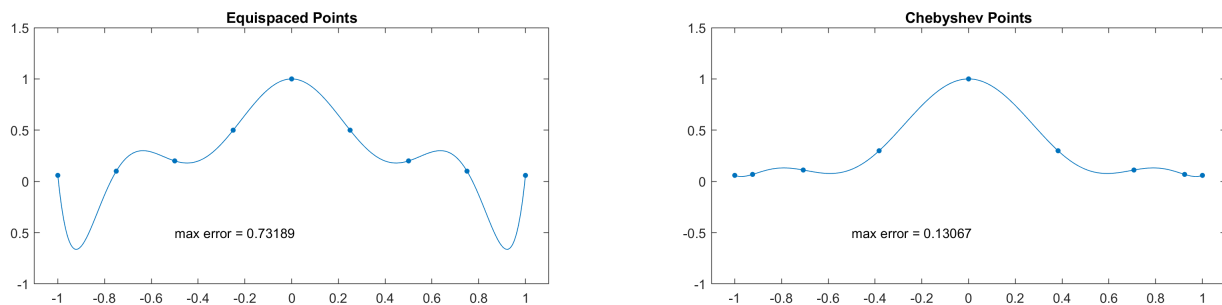


Figure 2:  $N = 8$

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<sup>1</sup>I accidentally did this problem and didn't want to delete all of the work, so I kept it in.

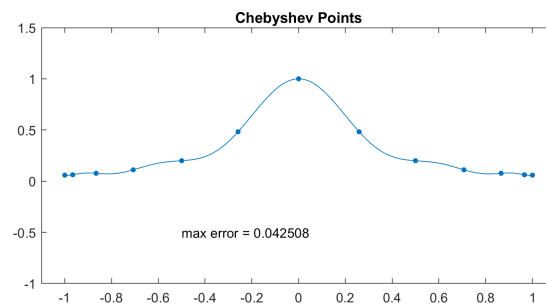
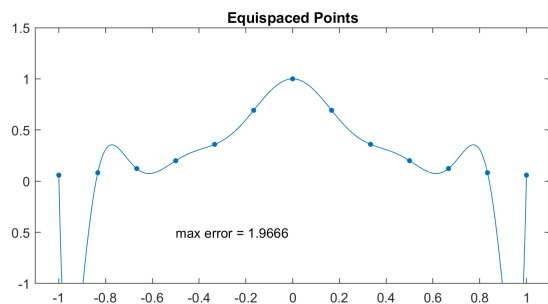


Figure 3:  $N = 12$

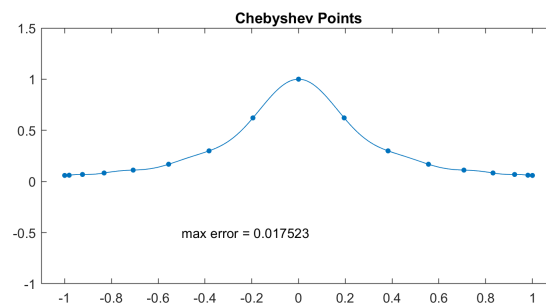
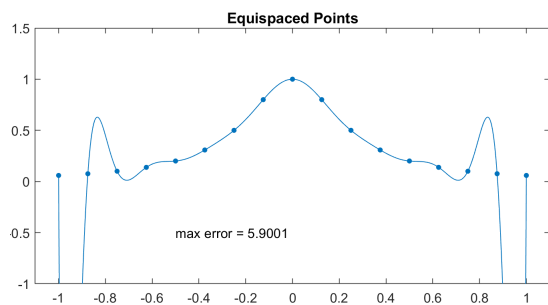


Figure 4:  $N = 16$

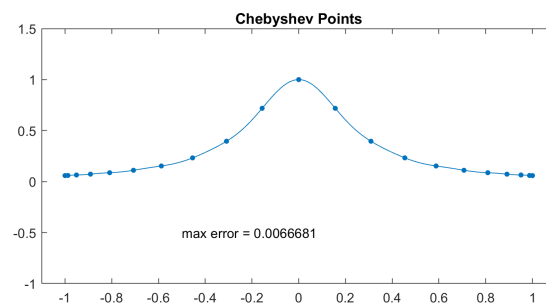
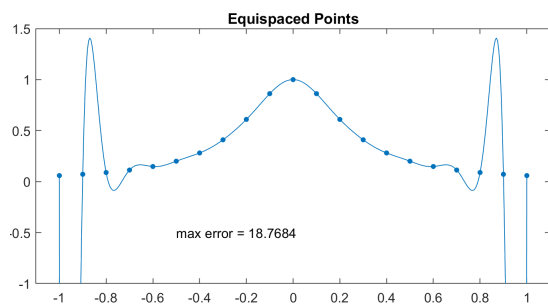


Figure 5:  $N = 20$

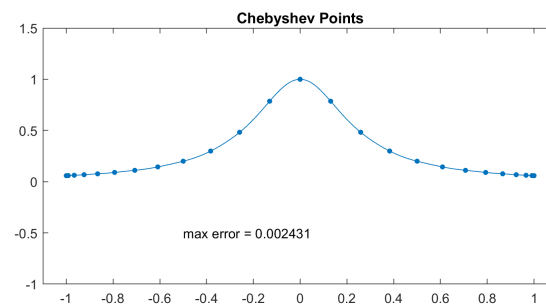
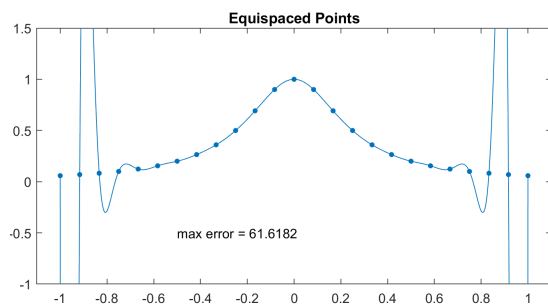


Figure 6:  $N = 24$

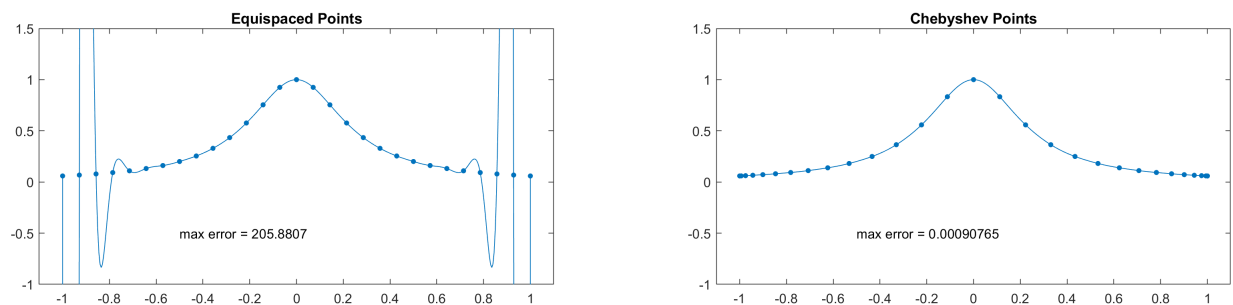
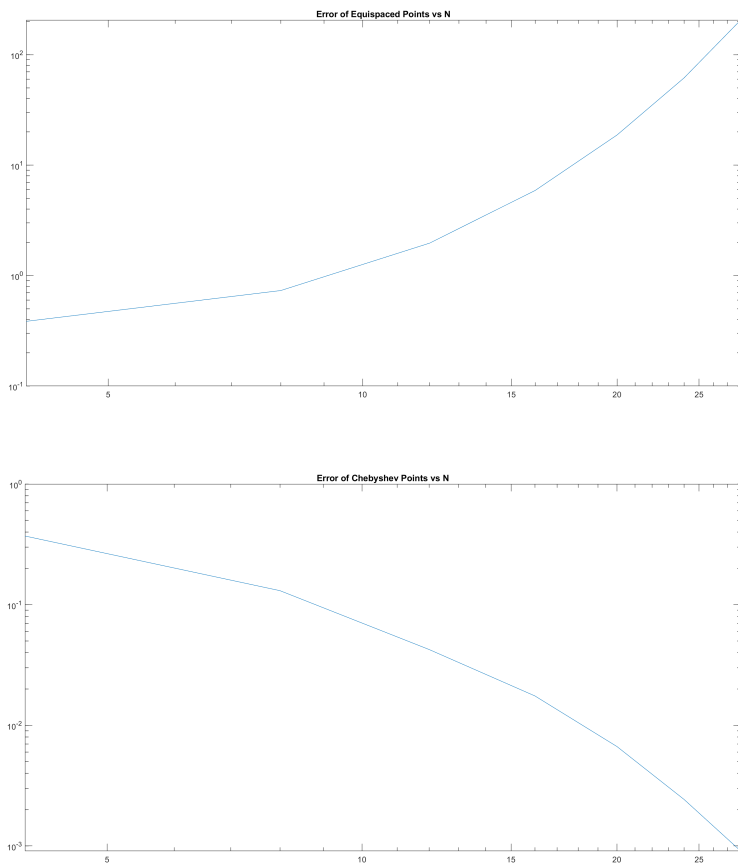


Figure 7:  $N = 28$

Now, looking at the two plots of the error vs  $N$ , we see that for the equidistal points, there is no convergence. Rather, there is divergence towards infinity and this divergence happens exponentially. Similarly, for the Chebyshev nodes, there is an exponential plotting, however, this is exponentially convergent.



```

1 % Stephanie Klumpe
2 % Problem 5.1 edited code
3
4 clear
5 close all
6 clc
7
8 error = zeros(2,7);           %% Set up an error matrix to hold the max errors
9 counter = 1;                  %% Counter used for indexing
10 xx = -1:.005:1; clf          %% x space
11 v=1; %% Used to split the above error matrix into the two different errors
12 Nval=[4 8 12 16 20 24 28];    %% N-value vector
13
14 for N = Nval
15
16     for i = 1:2
17
18         if i==1, s = 'Equispaced Points'; x = -1 + 2*(0:N)/N; end
19         if i==2, s = 'Chebyshev Points'; x = cos(pi*(0:N)/N); end
20         subplot(2,2,i)
21         u = 1./(1+16*x.^2);
22         uu = 1./(1+16*xx.^2);
23         p = polyfit(x,u,N);           % interpolation
24         pp = polyval(p,xx);           % evaluation of interpolant
25         plot(x,u, '.', 'markersize',13)
26         hold off
27         line(xx,pp)
28         axis([-1.1 1.1 -1 1.5]), title(s)
29         error(i,counter) = norm(uu-pp,inf);
30         text(-.5,-.5,['max error = ' num2str(error(i,counter))])
31
32     end
33
34     err1=error(1:v,:);              %% Max error vector of equispaced
35     err2=error(v+1:end,:);           %% Max error vector for the Cheb nodes
36     figure                           %% Opens new figure for each of the different N-values
37     counter=counter+1;
38
39 end
40
41 loglog(Nval,err1)
42 title('Error of Equispaced Points vs N')
43 figure
44 loglog(Nval,err2)
45 title('Error of Chebyshev Points vs N')

```

5.3. Let  $E_N = \inf_p \|p(x) - e^x\|_\infty$ , where  $\|f\|_\infty = \sup_{x \in [-1, 1]} |f(x)|$ , denote the error in degree  $N$  minimax polynomial approximation to  $e^x$  on  $[-1, 1]$ . (a) One candidate approximation  $p(x)$  would be the Taylor series truncated at degree  $N$ . From this approximation, derive the bound  $E_N < ((N+2)/(N+1))/(N+1)!$  for  $N \geq 0$ . (b) In fact, the truncated Taylor series falls short of optimal by a factor of about  $2^N$ , for it is known (see equation (6.75) of [Mei67]) that as  $N \rightarrow \infty$ ,  $E_N \sim 2^{-N}/(N+1)!$ . Modify Program 9 to produce a plot showing this asymptotic formula, the upper bound of (a), the error when  $p(x)$  is obtained from interpolation in Chebyshev points, and the same for equispaced points, all as a function of  $N$  for  $N = 1, 2, 3, \dots, 12$ . Comment on the results.

We know that the Taylor series expansion of  $e^x$  about  $x = 0$  is given by  $\sum \frac{x^n}{n!}$ . So, the truncated series is  $1 + x + \frac{x^2}{2} + \dots + \frac{x^N}{N!}$ . Hence,  $|p(x) - e^x| = |R_N(x)|$  where  $R_N(x)$  is the remainder of the exact Taylor expansion of  $e^x$ . We also know that such an expansion exists as  $e^x$  is an analytic function. So,

$$\begin{aligned} E_N &= \sup_{x \in [-1, 1]} \left| \sum_{k=N+1}^{\infty} \frac{x^k}{k!} \right| \\ &= \sum_{k=1}^{\infty} \frac{1}{(N+k)!} \\ &= \frac{1}{(N+1)!} \left( 1 + \frac{1}{N+2} + \frac{1}{(N+2)(N+3)} + \dots \right) \\ &< \frac{1}{(N+1)!} \left( \sum_{k=0}^{\infty} \frac{1}{(N+2)^k} \right) \end{aligned}$$

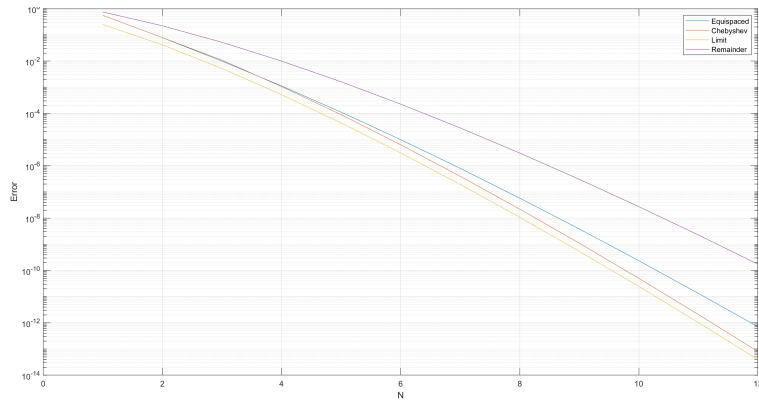
Here, we have a geometric series, so we get the equality

$$\begin{aligned} &= \frac{1}{(N+1)!} \frac{1}{1 - \frac{1}{N+2}} \\ &= \frac{1}{(N+1)!} \frac{1}{\frac{N+2}{N+2} - \frac{1}{N+2}} \\ &= \frac{N+2}{N+1} \frac{1}{(N+1)!} \end{aligned}$$

as desired.

Now, plotting the error bound we found, the known error bound, and the error of the approximations of  $e^x$  yields us graph:

```
1 % Stephanie Klumpe
2 % Problem 5.3 edited code
3
```



```

4 clear
5 close all
6 clc
7
8 Nspace = 1:12;
9 xx = -1.01:.005:1.01; clf
10
11 limerr = @(N) 1./(factorial(N+1).*2.^N);           % Define the known err and
12 remerr = @(N) ((N+2)./(N+1))./factorial(N+1);      % the remainder err as
13 polyerr = zeros(2, length(Nspace));               % fxns and the polyerr as
14                                                    % 2x12 matrix for both
15                                                    % approximations
16 for n = 1:length(Nspace)
17     N=Nspace(n);
18     for i = 1:2
19         if i==1, s = 'Equispaced Points'; x = -1 + 2*(0:N)/N; end
20         if i==2, s = 'Chebyshev Points'; x = cos(pi*(0:N)/N); end
21
22         u = exp(x);
23         uu = exp(xx);
24         p = polyfit(x,u,N);                         % interpolation
25         pp = polyval(p,xx);                         % evaluation of interpolant
26         polyerr(i,n) = norm(uu-pp,inf);             % fill in polyerr matrix for the two
27                                                    % types and the error values
28
29     end
30 end
31
32 hold on;
33 grid on;
34
35
36 title('foobar')
37 semilogy(Nspace,remerr(Nspace));                   % semilog plots of N vs the errors
38 semilogy(Nspace,polyerr(1,:));
39 semilogy(Nspace,limerr(Nspace));
40 semilogy(Nspace,polyerr(2,:));
41
42 print('5_3.png', '-dpng')

```

6.1. If  $x_0, x_1, \dots, x_N \in \mathbb{R}$  are distinct, then the cardinal function  $p_j(x)$  defined by

$$p_j(x) = \frac{1}{a_j} \prod_{k=0, \neq j}^N (x - x_k), \quad a_j = \prod_{k=0, \neq j}^N (x_j - x_k)$$

is the unique polynomial interpolant of degree  $N$  to the values 1 at  $x_j$  and 0 at  $x_k$ ,  $k \neq j$ . Take the logarithm and differentiate to obtain

$$p'_j(x) = p_j(x) \sum_{k=0, \neq j}^N (x - x_k)^{-1},$$

and derive the formulas

$$D_{ij} = \frac{1}{a_j} \prod_{k=0, \neq j}^N (x_i - x_k) = \frac{a_i}{a_j(x_i - x_j)} \quad (i \neq j)$$

and

$$D_{jj} = \sum_{k=0, \neq j}^N (x_j - x_k)^{-1}$$

Letting  $p_j(x)$  and  $a_j$  be as given above, we take the natural logarithm of both sides. This gives us

$$\begin{aligned} \ln(p_j(x)) &= \ln\left(\prod_{k=0, \neq j}^N \frac{(x - x_k)}{(x_j - x_k)}\right) = \sum_{k=0, \neq j}^N \ln\left(\frac{x - x_k}{x_j - x_k}\right) \\ &= \sum_{k=0, \neq j}^N \ln(x - x_k) - \sum_{k=0, \neq j}^N \ln(x_j - x_k) \end{aligned}$$

Now differentiating both sides yields

$$\frac{p'_j(x)}{p_j(x)} = \sum_{k=0, \neq j}^N \frac{1}{(x - x_k)} - 0$$

which gives us the desired equation

$$p'_j(x) = p_j(x) \sum_{k=0, \neq j}^N (x - x_k)^{-1}$$

6.8. Let  $D_N$  be the usual Chebyshev differentiation matrix. Show that the power  $(D_N)^{N+1}$  is identically equal to zero. Now try it on the computer for  $N = 5$  and 20 and report the computed 2-norms  $\|(D_5)^6\|_2$  and  $\|(D_{20})^{21}\|_2$ . Discuss.

We know that the Chebyshev differentiation matrix,  $D_N$ , is a result of differentiating the  $N^{th}$  degree Chebyshev polynomial. By the nature of the polynomials, we have that they are given by  $\sum_{i=1}^N c_i x^i$  where  $c_i$  are the coefficients found by interpolating through the Chebyshev nodes. So, taking the derivative would give us an  $(N-1)^{th}$  degree polynomial. To find the second order differentiation matrix, we apply  $D_N$  to  $D_N$  to get  $D_N^2$ . That is, we take the second derivative of the Chebyshev polynomial. Continuing the process, we see that

$$\left(\sum_{i=1}^N c_i x^i\right)^{(N)} = c_N$$

Hence,

$$\left(\sum_{i=1}^N c_i x^i\right)^{(N+1)} = (c_N)' = 0$$

So, applying  $D_N$  to  $(D_N)^N$  gives us  $(D_N)^{N+1} = 0$  as desired.

Now, with the following code, we see that we do get a number very close to zero relative to Matlab's precision for  $N = 5$ , however, we get an astronomically large number for  $N = 20$ . This is due to the roundinfg and floating number capabilities for the program. So while theoretically, the matrix to the 21st power would yield 0, that doesn't quite work in this particular instance of numerical computing.



```
1 % Stephanie Klumpe
2 % Problem 6.8
3 % (Cheb matrix_N)^(N+1)=0 code
4
5 clear
6 close all
7 clc
8
9 [Df,x] = cheb(5);           % Define the cheb matrices
10 [Dt,y] = cheb(20);
11
12 D6 = (Df)^6;               % Raise them to powers
13 D21 = (Dt)^(20);
14
15 D5err = norm(D6,2)         % Compute the L2 norm of the powers
16 % 6.0832e-11
17 D20err = norm(D21,2)
18 % 1.2906e+24
```

7.1. Modify Program 13 so that instead of polyval and polyfit, it uses the more stable formula of barycentric interpolation

$$p(x) = \sum_{j=0}^N \frac{a_j^{-1} u_j}{x - x_j} / \sum_{j=0}^N \frac{a_j^{-1}}{x - x_j}$$

where  $\{a_j\}$  are defined by (6.7). Experiment with various interpolation problems (such as that of Exercise 5.1) and find evidence of the enhanced stability of this method.

Using the barycentric interpolation, we have the following code. We test it with three different conditions for our ODE and get these three graphs. We can see that this interpolation method works well and is quite robust.

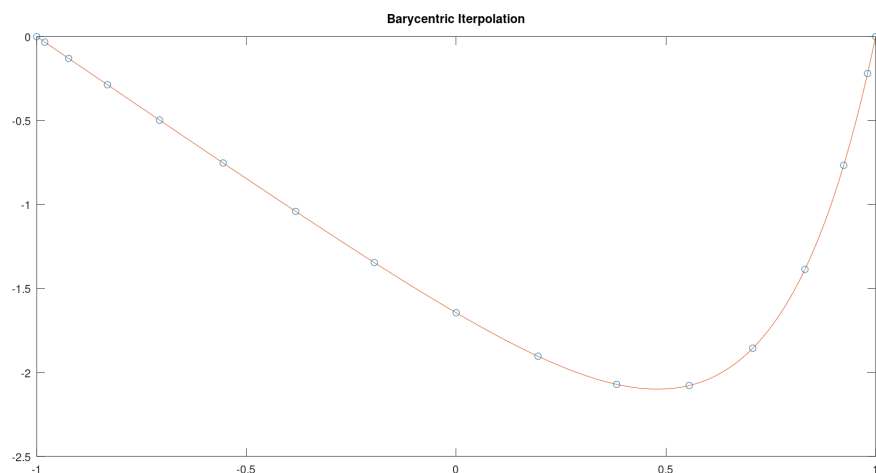


Figure 8:  $e^{4x}$

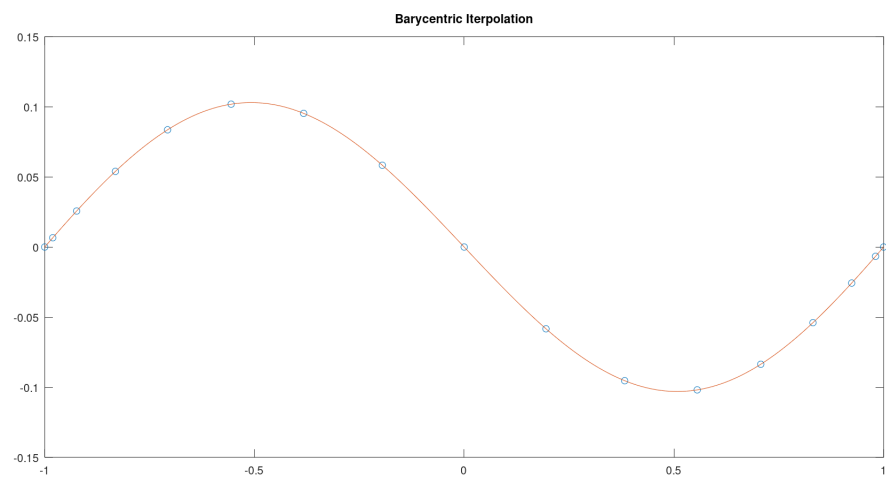


Figure 9:  $\sin(x)$

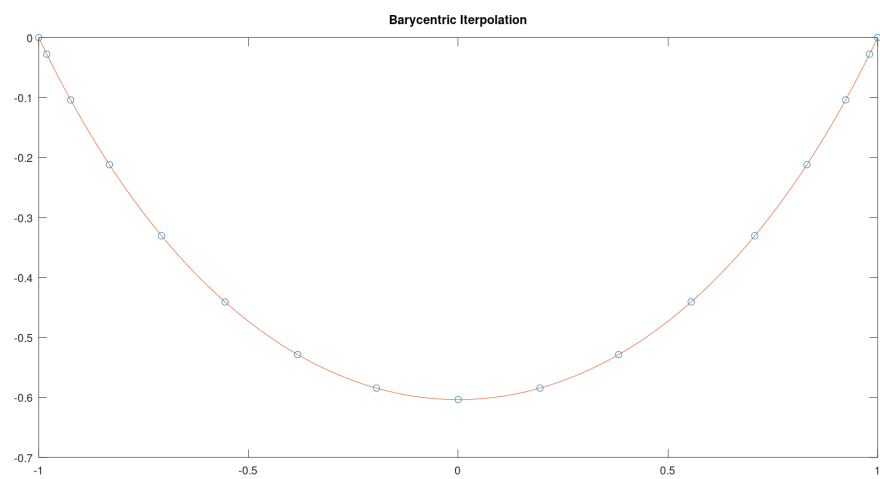


Figure 10:  $e^{x^2}$

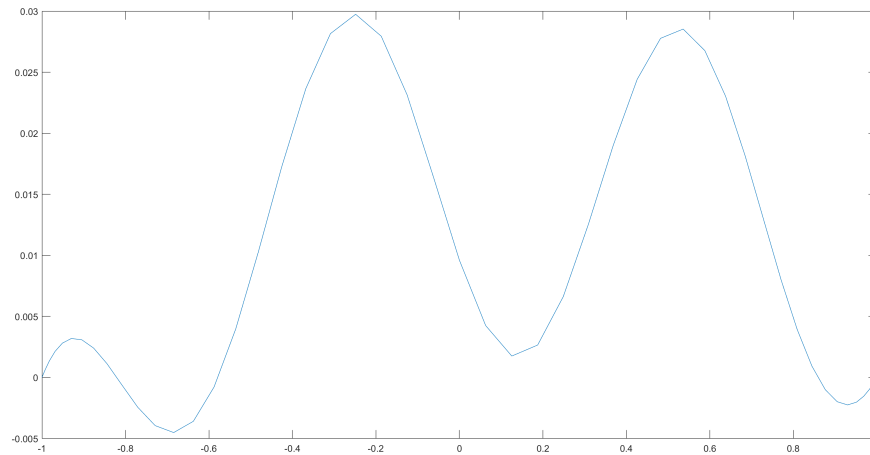
```

1 % Stpehnaie Klumpe
2 % Problem 7.1
3
4 clear
5 close all
6 clc
7
8 N = 16;
9 [D,x] = cheb(N);           % Define the Cheb matrix for both first and
10 D2 = D^2;                 % second order
11 D2 = D2(2:end-1, 2:end-1);
12
13 f = exp(4*x(2:N));
14 %f = sin(3*x(2:N));       % Different functions to test with
15 %f = exp((x(2:N)).^2);
16 u = D2\f;
17 u = [0; u; 0];           % Define our ODE and plot our Cheb nodes on our
18 plot(x,u,'o')             % solution
19 xx = -1:0.01:1;
20
21 ainv = ones(N+1,1);
22 denom = zeros(length(xx),1); % Define our a^-1, numerator, and ...
    denominator
23 num = zeros(length(xx),1);   % vectors
24
25 for i=1:N+1
26     for k=1:N+1
27         if k ≠ i
28             ainv(i) = ainv(i)*(x(i) - x(k)); % Fill out the a^-1 vector
29         end
30     end
31 end
32
33
34 for i = 1:N+1
35
36     denom = denom + ainv(i)^(-1)./(xx.' - x(i)); % Fill out the num and
37     num = num + ainv(i)^(-1)*u(i)./(xx.' - x(i)); % denom vectors
38
39
40 end
41
42 num = num(2:end-1);         % Take off the ends of the num vector and ...
    replace
43 num = [0;num;0];           % them with the boundary conditions
44
45 u = num./denom;
46 hold on
47 plot(xx, u, '-')
48 title('Barycentric Iterpolation')

```

7.2. Solve the boundary value problem  $u_{xx} + 4u_x + e^x u = \sin(8x)$  numerically on  $[-1, 1]$  with boundary conditions  $u(\pm 1) = 0$ . To ten digits of accuracy, what is  $u(0)$ ?

For this problem, we have both a first order and a second order term in our equation, so we will use a first and second order Chebyshev matrix. After running through the code below, we have that  $u(0) \approx 0.009597857230$  and we also get the following graph with  $N = 50$ .



```

1 % Stephanie Klumpe
2 % Problem 7.2
3
4 clear
5 close all
6 clc
7
8 N = 50;
9 [D,x] = cheb(N);
10 D2 = D^2; % Here, we define our Cheb points and
11 D2 = D2(2:end-1,2:end-1); % our 1st and 2nd order Cheb diff
12 D1 = D(2:end-1,2:end-1); % matrices
13
14 evec = exp(x);
15 evec(1) = [];
16 evec(end) = [];
17 f = sin(8*x); % We set up our RHS and our e^x vectors
18 f(1) = [];
19 f(end) = [];
20 ematr = diag(evec);
21
22 U = D2+4*D1+ematr;
23 u = U\f; % Solving for our function u(x)
24 u = [0;u;0];
25
26 fprintf('u(0)=%0.12f',u(26));
27 plot(x,u)

```

8.3. Modify Program 12 (p. 57) to make use of `chebfft` instead of `cheb`. The results should be the same as in Output 12, except for rounding errors. Are the effects of rounding errors smaller or larger than before?

Below are the graph outputs of program 12, the first of which is using `cheb` and the second using `chebfft`:

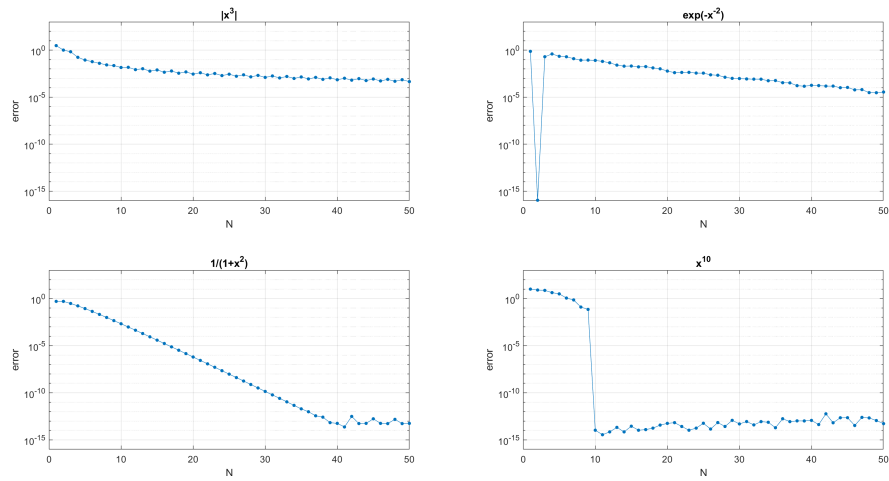


Figure 11: `cheb`

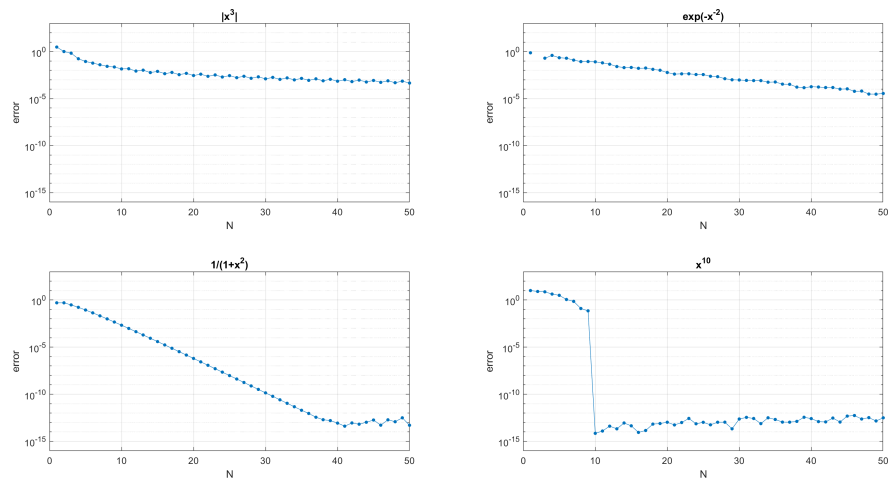


Figure 12: `chebfft`

We see that the round off error is the only difference between the two graphs. It can also be seen that the rounding error for the `chebfft` function is slightly less than that of the regular `cheb` function.

```

1 % Stephanie Klumpe
2 % Problem 8.3 edited code
3
4 clear
5 close all
6 clc
7
8 % Compute derivatives for various values of N:
9 Nmax = 50; E = zeros(3,Nmax);
10 for N = 1:Nmax
11     [D,x] = cheb(N);
12     v = abs(x).^3; vprime = 3*x.*abs(x); % 3rd deriv in BV
13     E(1,N) = norm(chebfft(v)-vprime,inf);
14     v = exp(-x.^(-2)); vprime = 2.*v./x.^3; % C-infinity
15     E(2,N) = norm(chebfft(v)-vprime,inf);
16     v = 1./(1+x.^2); vprime = -2*x.*v.^2; % analytic in [-1,1]
17     E(3,N) = norm(chebfft(v)-vprime,inf);
18     v = x.^10; vprime = 10*x.^9; % polynomial
19     E(4,N) = norm(chebfft(v)-vprime,inf);
20 end % We replaced the D*v in the norm
21 % computation with chebfft(v)
22
23 % Plot results:
24 titles = {'|x^3|', 'exp(-x^{-2})', '1/(1+x^2)', 'x^{10}'}; clf
25 for iplot = 1:4
26     subplot(2,2,iplot)
27     semilogy(1:Nmax,E(iplot,:),'.','markersize',12)
28     line(1:Nmax,E(iplot,:))
29     axis([0 Nmax 1e-16 1e3]), grid on
30     set(gca,'xtick',0:10:Nmax,'ytick',(10).^(-15:5:0))
31     xlabel N, ylabel error, title(titles(iplot))
32 end

```



8.5. Find a way to modify your program of Exercise 8.4, as in Exercise 3.8 but now for a second-order problem, to make use of matrix exponentials rather than time discretization. What effect does this have on the computation time?

Using the code that we worked through in class, we have the following code. From the code, we have that the elapsed time is about 0.0065 seconds. For the original code, adding in the tic/toc function, we get that the average elapsed time is about 0.5 seconds.

```

1 % Stephanie Klumpe
2 % Problem 8.5
3
4 clear
5 close all
6 clc
7
8 tic
9
10 % Grid and initial data:
11 N = 24;
12 x = cos(pi*(0:N)/N);
13 y = x';
14 dt = 6/N^2;
15 [D,x] = cheb(N);
16 D2 = D^2;
17
18 D2 = D2(2:N,2:N);
19 I = eye(N-1);
20 L = kron(I,D2) + kron(D2,I);
21
22 [xx,yy] = meshgrid(x,y);
23 plotgap = round((1/3)/dt);
24 dt = (1/3)/plotgap;
25 vv = exp(-40*((xx-.4).^2 + yy.^2));
26 vv=vv(2:N,2:N);
27 vvold = vv;
28
29 % Time-stepping by leap frog formula:
30 for n = 0:3*plotgap
31     t = n*dt;
32
33     U=vv(:); RHS=L*U; RHS=reshape(RHS,N-1,N-1);
34     vvnew = 2*vv - vvold + dt^2*RHS;
35     vvold = vv;
36 end
37
38 toc
39 % Elapsed time was about 0.0065 seconds

```

8.6. Write a code `chebfft2` for second-order differentiation by the FFT, and show by examples that it matches the results obtained by matrices, apart from rounding errors.<sup>2</sup>

Here, we used the functions  $\sin(x)$ ,  $e^x$ , and  $e^{-x^2}$  as examples to demonstrate the `chebfft2` function. In order to write this function, all we needed to do is repeat the FFT, inverse FFT, and deriving the algebraic polynomial steps just on the derivative vector. So, we get the following graphs.

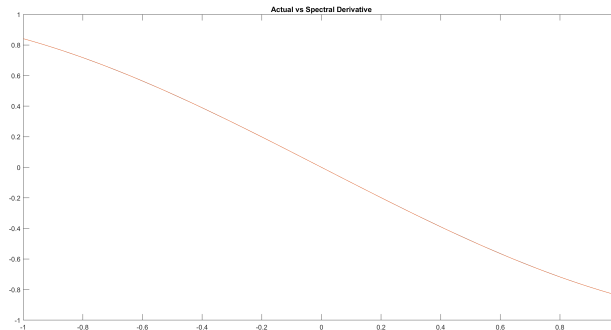


Figure 13:  $\sin(x)$

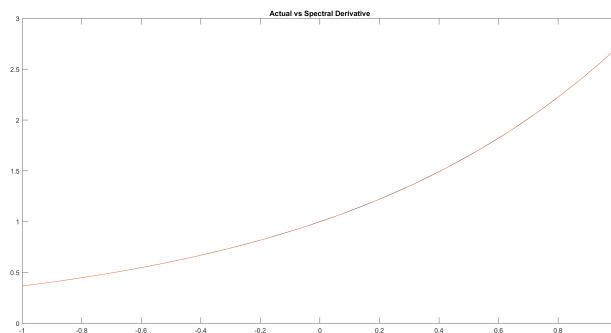


Figure 14:  $e^x$

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<sup>2</sup>Again, this was not an assigned problem, however I did quite a bit of work for it and didn't want to delete it.

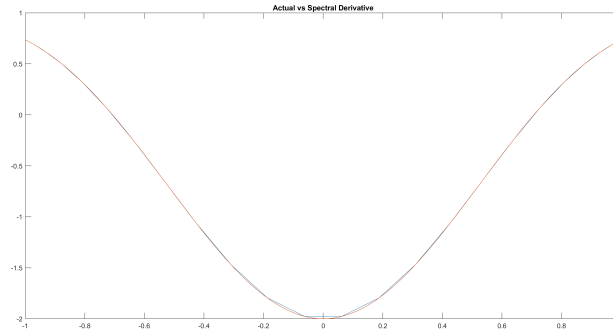


Figure 15:  $e^{-x^2}$

```

1 % Stephanie Klumpe
2 % Problem 8.5
3 % chebfft2
4
5 clear
6 close all
7 clc
8
9 t=-1:0.001:1;
10 [D,x]=cheb(25); % Compute Cheb points
11 v=sin(x); % Choose a function
12 %v=exp(x);
13 %v=exp(-x.^2);
14 d2v=-sin(t); % Define the second derivative
15 %d2v=exp(t);
16 %d2v=exp(-t.^2).*(4.*t.^2-2);
17 dw=chebfft2(v); % Call the new function
18 plot(x,dw) % Plot the actual deriv and the
19 hold on % spectral deriv to compare
20 plot(t,d2v)
21 title('Actual vs Spectral Derivative')
22
23
24
25 function dw = chebfft2(v)
26 N = length(v)-1; if N==0, w=0; return, end
27 x = cos((0:N)'*pi/N);
28 ii = 0:N-1;
29 v = v(:); V = [v; flipud(v(2:N))]; % transform x -> theta
30 U = real(fft(V));
31 W = real(ifft(1i*[ii 0 1-N:-1]'.*U));
32 w = zeros(N+1,1);
33 w(2:N) = -W(2:N)./sqrt(1-x(2:N).^2); % transform theta -> x
34 w(1) = sum(ii'.^2.*U(ii+1))/N + .5*N*U(N+1);
35 w(N+1) = sum((-1).^(ii+1)'.*ii'.^2.*U(ii+1))/N + ...
36 .5*(-1)^(N+1)*N*U(N+1);
37 dV=[w; flipud(w(2:N))]; % Repeat the above process
38 dU=real(fft(dV)); % by defininig a vector to be
39 dW = real(ifft(1i*[ii 0 1-N:-1]'.*dU)); % the derivative vector. Then

```

```

40     dw = zeros(N+1,1);                                % compute the spectral deriv.
41     dw(2:N) = -dW(2:N)./sqrt(1-x(2:N).^2);
42     dw(1) = sum(ii'.^2.*dU(ii+1))/N + .5*N*U(N+1);
43     dw(N+1) = sum((-1).^(ii+1)'.*ii'.^2.*dU(ii+1))/N + ...
44               .5*(-1)^(N+1)*N*dU(N+1);
45     end
46
47 % From this, we can say that if we repeate the same idea as above
48 % n times, we can get the nth derivative using Cheb spectral diff via FFT.

```