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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? ¹

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

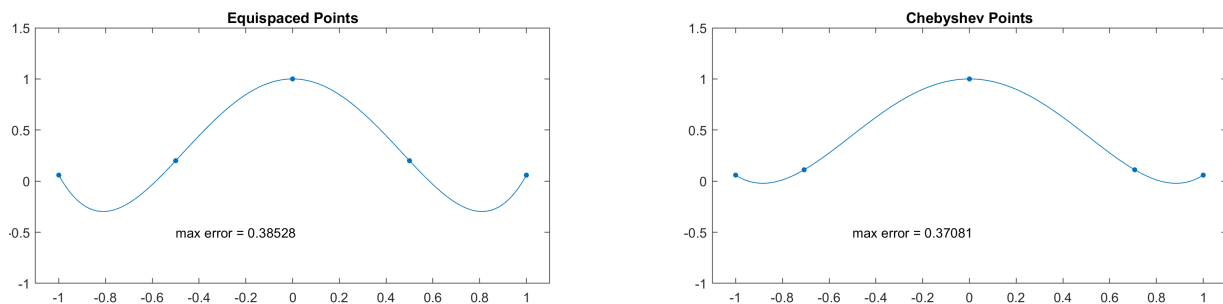


Figure 1: $N = 4$

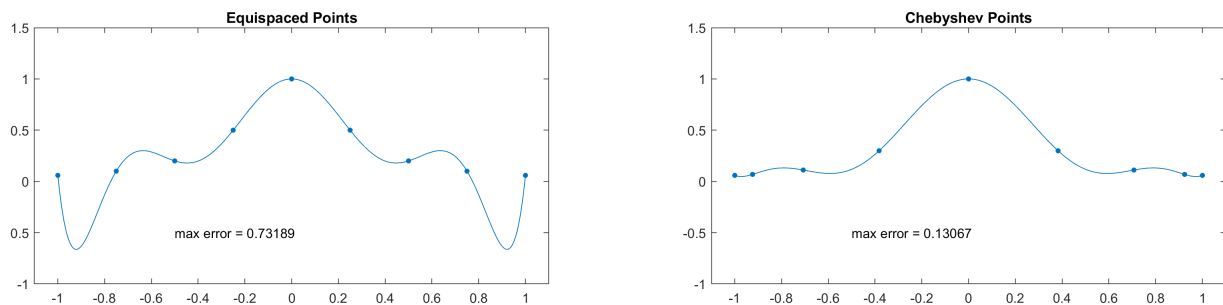


Figure 2: $N = 8$

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

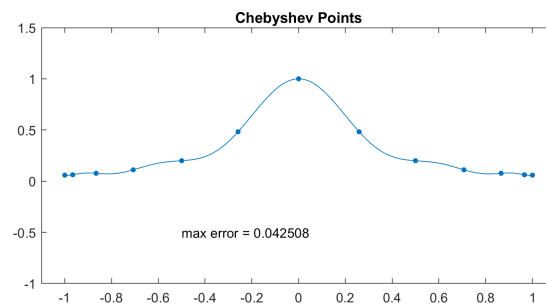
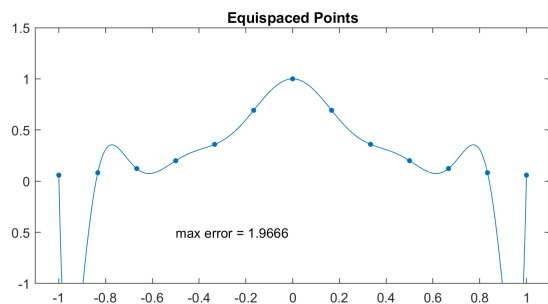


Figure 3: $N = 12$

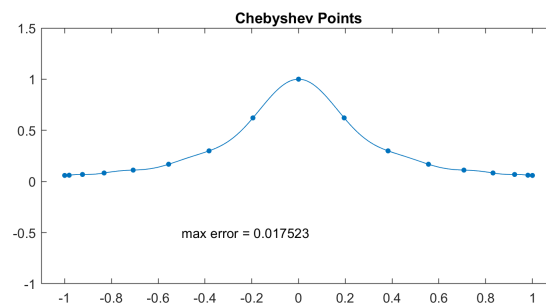
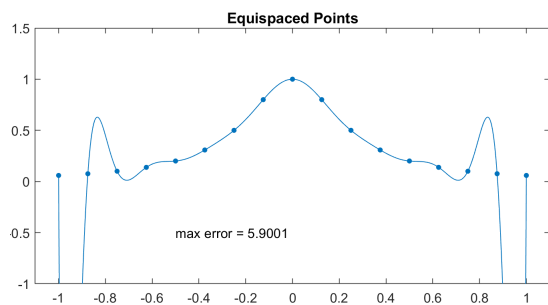


Figure 4: $N = 16$

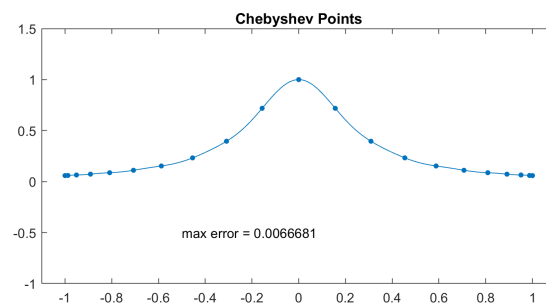
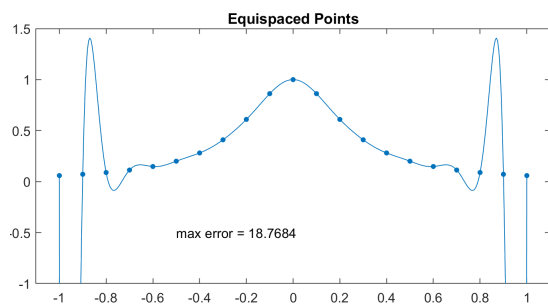


Figure 5: $N = 20$

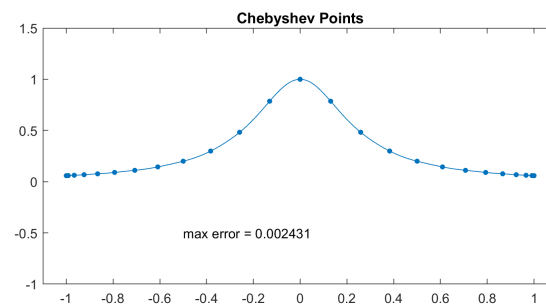
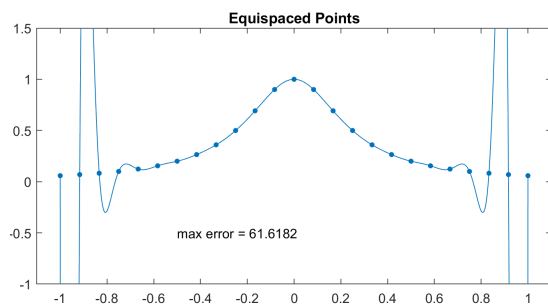


Figure 6: $N = 24$

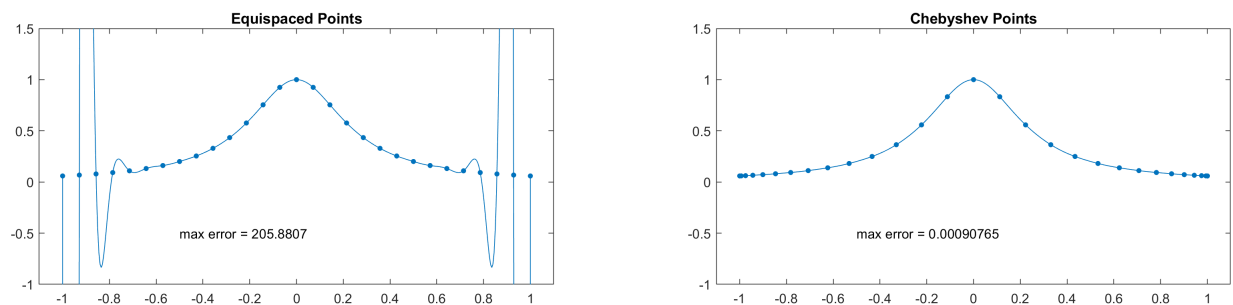
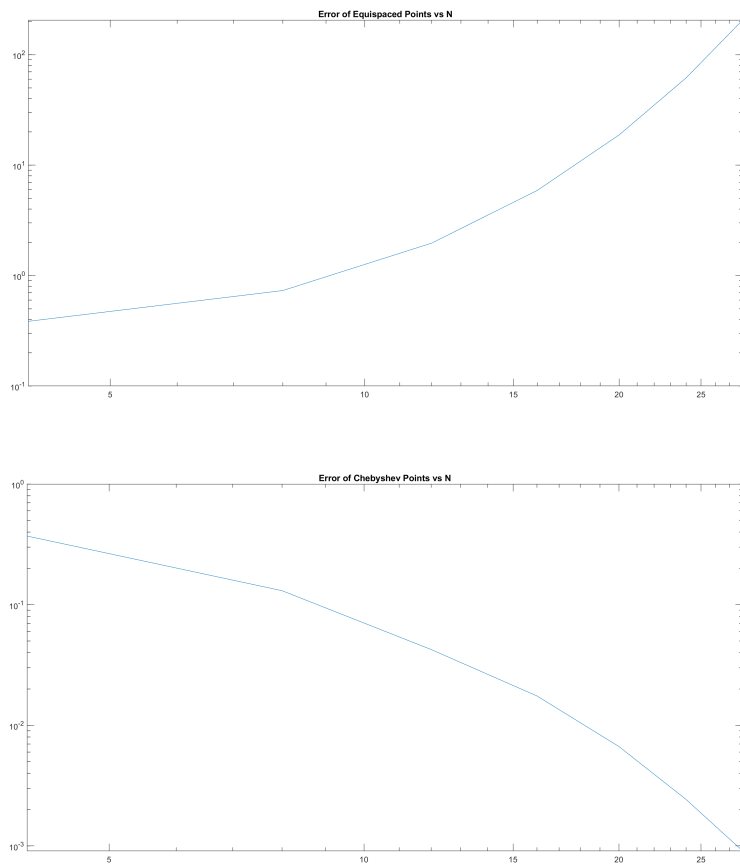


Figure 7: $N = 28$

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 5.3 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,

$$E_N = \sup_{x \in [-1, 1]} \left| \frac{1}{n!} \int_0^x e^t (x-t)^n dt \right|$$

using the integral form of the remainder. Now,

$$\begin{aligned} E_N &= \sup_{x \in [-1, 1]} \frac{1}{n!} \left| \int_0^x e^t (x-t)^n dt \right| \leq \sup_{x \in [-1, 1]} \frac{1}{n!} \int_0^x |e^t (x-t)^n| dt \\ &\leq \sup_{x \in [-1, 1]} \frac{1}{n!} \int_0^x e |(x-t)^n| dt = \sup_{x \in [-1, 1]} \frac{e}{n!} \left| \frac{x^{n+1}}{(n+1)} \right| = \frac{e}{(n+1)!} \end{aligned}$$

```

1 % Stephanie Klumpe
2 % Problem 5.3 edited code
3
4 clear
5 close all
6 clc
7
8 N=16;
9 xx = -1:.005:1; clf
10 for i = 1:2
11     if i==1, s = 'equispaced points'; x = -1 + 2*(0:N)/N; end
12     if i==2, s = 'Chebyshev points'; x = cos(pi*(0:N)/N); end
13     subplot(2,2,i)
14     u = 1./(1+16*x.^2);
15     uu = 1./(1+16*xx.^2);
16     p = polyfit(x,u,N); % interpolation
17     pp = polyval(p,xx); % evaluation of interpolant
18     plot(x,u, '.', 'markersize',13)
19     hold off
20     line(xx,pp)
21     axis([-1.1 1.1 -1 1.5]), title(s)
22     error(N,i) = norm(uu-pp,inf);
23     text(-.5,-.5,['max error = ' num2str(error(N,i))])
24 end

```

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.

Well,

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.

Well,

```

1 % Stephanie Klumpe
2 % Problem 7.1 edited code
3
4 clear
5 close all
6 clc
7
8 N = 16;
9 [D,x] = cheb(N);
10 D2 = D^2;
11 D2 = D2(2:N,2:N); % boundary conditions
12 f = exp(4*x(2:N));
13 u = D2\f; % Poisson eq. solved here
14 u = [0;u;0];
15 clf, subplot('position',[.1 .4 .8 .5])
16 plot(x,u, '.', 'markersize',16)
17 xx = -1:.01:1;
18 uu = polyval(polyfit(x,u,N),xx); % interpolate grid data
19 line(xx,uu)
20 grid on
21 exact = ( exp(4*xx) - sinh(4)*xx - cosh(4) )/16;
22 title(['max err = ' num2str(norm(uu-exact,inf))], 'fontsize',12)
23
24 %inva = 1./prod(x_j-x_k)
25 %uu=
26
27 % M=length(data); N=length(x);
28 % Compute the barycentric weights
29 % X= repmat(data(:,1),1,M);
30 % matrix of weights
31 % W= repmat(1./prod(X-X.'+eye(M),1),N,1);
32 % Get distances between nodes and interpolation points
33 % xdists= repmat(x,1,M)- repmat(data(:,1).',N,1);
34 % Find all of the elements where the interpolation point is on a node
35 % [fixi,fixj]=find(xdists==0);
36 % Use NaNs as a place-holder
37 % xdists(fixi,fixj)=NaN;
38 % H=W./xdists;
39 % Compute the interpolated polynomial
40 % p=(H*data(:,2))./sum(H,2);
41 % Replace NaNs with the given exact values.
42 % p(fixi)=data(fixj,2);

```

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 $u(0)$?

Well,

```
1 % Stephanie Klumpe
2 % Problem 7.2
3
4 clear
5 close all
6 clc
7
8 xx = -1:.01:1;
9 u=zeros(size(xx));
10 u(-1)=0;
11 u(1)=0;
```

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:

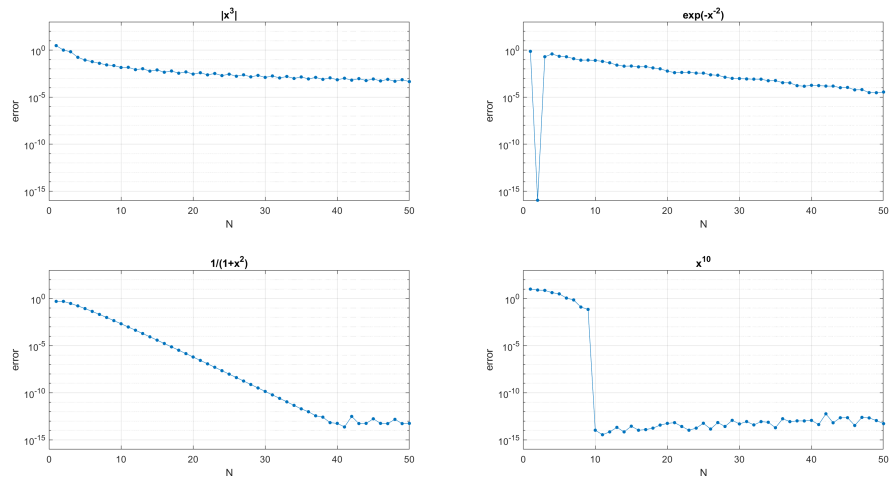


Figure 8: cheb

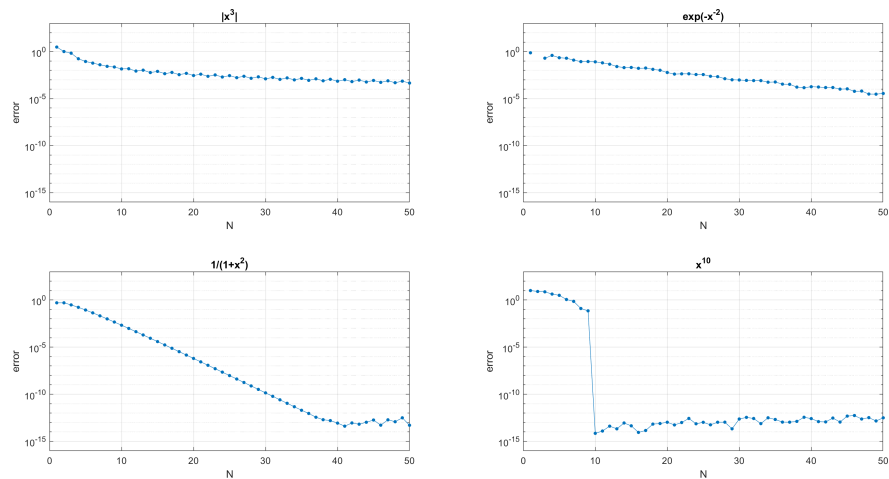


Figure 9: chebfft

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. 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.

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.

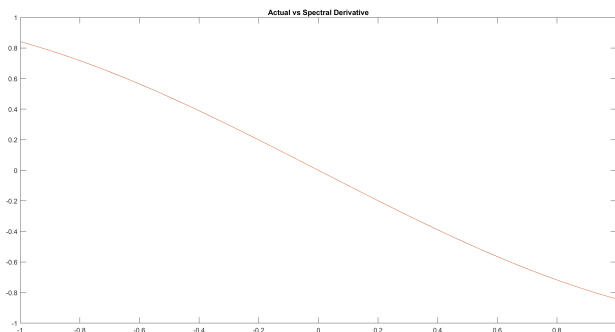


Figure 10: $\sin(x)$

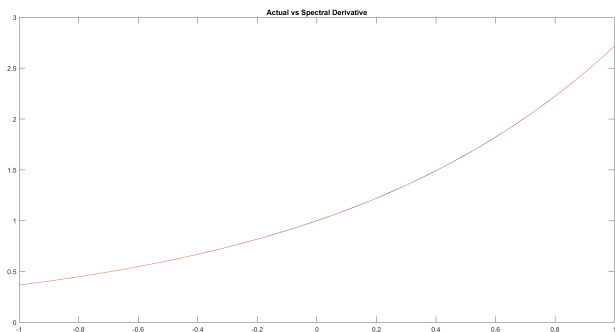


Figure 11: e^x

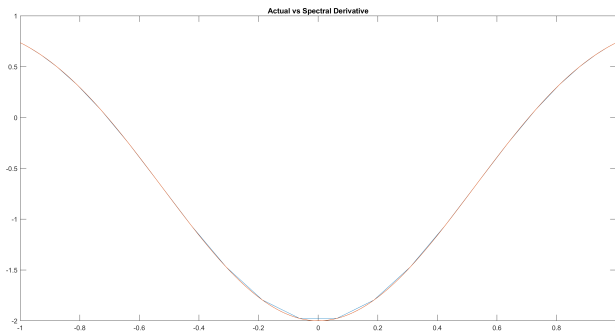


Figure 12: e^{-x^2}

And we see that the matrices also provide the same outputs barring the roundoff errors.

```

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*dU(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.

```