## 3 INTERPOLATION

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## Initialization

```
% reduce needless whitespace
format compact
% reduce irritations
more off
% start a diary
%diary lectureN.txt
```


## INTERPOLATION.

Probably, you have already done interpolation before in other courses. In fact, if you are in ME Tools, you are doing it there right now. The next few sections will explain how you can do it much easier and better with Matlab.
As an example problem that requires interpolation, assume that we have placed a hot bar with its ends in contact with ice water. The temperature of the bar will then decay over time to 0 degrees Centigrade. We have measured the temperature of the center of the bar at 6 times spaced half a minute apart. Taking the first of these times as time zero, the measured data are:

| time: | 0 | 0.5 | 1 | 1.5 | 2 | minutes |
| :--- | :---: | :---: | :---: | :---: | :---: | :--- |
| Temperature: | 14.60 | 8.42 | 4.86 | 2.80 | 1.62 | Centigrade |

We will define Matlab arrays timeMeasured and TempMeasured as the six measured times and temperatures respectively.
(Note to some students. This is a lecture about interpolation, not heat conduction. You do not need to understand heat conduction to follow this lecture. All
you need to know that we want to interpolate the data above. If you want, you can think of them instead as tabulated values in a ME Tools table.)
Supposedly unknown to us, the exact temperature is given by

$$
T_{\text {exact }}=14.6 \exp (-1.1 t) ;
$$

We will pretend that we only know the measured temperatures. So we have to interpolate using only those measured data. But afterwards we will cheat and evaluate the errors using the exact function above. Just to see how well we are really doing interpolating.
To make that easier, we will create a function TempExactFun to evaluate the exact temperature that we pretend not to know. Since the function is very simple and not intended for more general use, we do not need to create a function file for it. Instead we can define TempExactFun as a "handle" to an anonymous function.

```
% define timeMeasured and TempMeasured as given
timeMeasured =[\begin{array}{llllll}{0}&{0.5}&{1}&{1.5}&{2]}\end{array}]
TempMeasured =[lllllll}14.60 8.42 4.86 2.80 1.62 [ ';'
% make TempExactFun a handle to an anonymous function
TempExactFun = @(t) 14.6*exp(-1.1*t);
disp(',')
```


## Plot to understand the problem better

Let's plot the measured five values versus the exact solution that we pretend not to know. Note that to plot a function, you need to create a set of plot points. These are different from the measured points and just used for plotting.

```
% generate 100 time values between 0 and 2
timePlot=linspace (0, 2,100);
% generate corresponding exact temperatures
TempExactPlot=TempExactFun(timePlot);
% create the plot, using circles for the measured points
plot(timePlot,TempExactPlot, '--k',...
    timeMeasured, TempMeasured, 'ok')
legend('Exact', 'Measured')
title('Measured and Exact Temperatures')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
disp(', ')
```



## Doing the interpolation

We would now like to be able to evaluate the temperature at times in between the measured five times. This is called "interpolation".
For example, let's assume that we want to know the temperature at time 0.7 , which is in between measured times 0.5 and 1 .
Matlab provides interp1 or spline to find it.

```
% let's evaluate T at t = 0.7 using two different methods
time=0.7
TempLinear=interp1(timeMeasured,TempMeasured, time )
TempSpline=spline(timeMeasured,TempMeasured,time)
% two reasonable values, but which one is best???
TempExact=TempExactFun(time)
disp('For a nice smooth curve, spline interpolation is')
disp('much more accurate than linear interpolation!')
errLinear=abs(TempLinear-TempExact)
errSpline=abs(TempSpline-TempExact)
disp(', )
```

```
time = 0.70000
TempLinear = 6.9960
```

```
TempSpline = 6.7513
TempExact = 6.7600
For a nice smooth curve, spline interpolation is
much more accurate than linear interpolation!
errLinear = 0.23601
errSpline = 0.0086708
```


## Compare the interpolations

```
% find the interpolated values at the plot times
TempLinearPlot = ...
    interp1(timeMeasured, TempMeasured, timePlot);
TempSplinePlot=...
        spline(timeMeasured,TempMeasured, timePlot);
% compare the interpolations in a plot
plot(timePlot,TempExactPlot, '--k', ...
    timeMeasured,TempMeasured, 'ok', ...
    timePlot, TempLinearPlot, 'r', ,..
    timePlot, TempSplinePlot, 'b')
legend('Exact','Measured','Linear','Spline')
title('Linear and Spline Interpolation')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
% compare the __maximum_ deviations
errLinearPlot=max(abs(TempLinearPlot-TempExactPlot))
errSplinePlot=max(abs(TempSplinePlot-TempExactPlot))
disp('The spline is everywhere much more accurate.')
disp(' ')
```

```
errLinearPlot = 0.42108
errSplinePlot = 0.017672
```

The spline is everywhere much more accurate.

## Extrapolation

Suppose that the time at which we want to know the temperature is $t=5$. This time is not inside the measured range from 0 to 2 . If that happens, we talk about extrapolation instead of interpolation.

Extrapolation is much trickier than interpolation.
For that reason, interp1 refuses to do it unless you specify an additional "extrap" parameter. Function spline will do it as is.


```
% evaluate the values at t=5
time=5
TempExact=TempExactFun(time)
TempLinear=interp1(timeMeasured,TempMeasured,time,...
    'linear', 'extrap')
TempSpline=spline(timeMeasured,TempMeasured, time)
disp('Extrapolation is usually bad news!')
disp(',')
% Note that both linear and spline values are bad, and
% that the spline is much worse than linear. But both
% values are useless.
```

```
time \(=5\)
TempExact \(=0.059667\)
TempLinear \(=-5.4600\)
TempSpline \(=-14.700\)
Extrapolation is usually bad news!
```


## SKIP: More on spline interpolation

Often you would want your spline to satisfy end conditions. For example, you might want it to have given derivatives at the ends. Or be periodic. Given derivatives at the ends can be achieved using 'spline' if you add the desired two values to the function values list. For more complicated cases, consider function 'csape'.

## NOISY DATA

What if the measured data have random errors? Suppose, for example, that the digital thermometer used to to measure the data only displays whole degrees C? Then the measured data:

```
Temperature: 14.60 8.42 4.86 2.80 1.62 Centigrade
```

become:
Temperature: $\begin{array}{lllllll}15 & 8 & 5 & 3 & 2 & \text { Centigrade }\end{array}$
Then what happens to our interpolations?

```
% correct the measured data list
TempMeasured=[[15 8 8 5 5 3 2 []';
% interpolate again at t=0.7
time=0.7
TempExact=TempExactFun(time)
TempLinear=interp1(timeMeasured,TempMeasured, time )
TempSpline=spline(timeMeasured,TempMeasured, time)
disp('Now the linear interpolation is actually better!');
errLinear=abs(TempLinear-TempExact)
errSpline=abs(TempSpline-TempExact)
% compare the interpolations in a plot
TempLinearPlot=...
    interp1(timeMeasured, TempMeasured, timePlot);
TempSplinePlot=\ldots
    spline(timeMeasured,TempMeasured, timePlot);
plot(timePlot,TempExactPlot,'--k', ...
        timeMeasured,TempMeasured, 'ok', ...
        timePlot,TempLinearPlot, 'r', ,..
        timePlot, TempSplinePlot, 'b')
legend('Exact','Measured','Linear', 'Spline')
title('Linear and Spline Interpolation, Noisy Data')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
```

```
% Because of the noise, the spline can be worse than
% linear. The spline may also start oscilating if things
% get really bad. Note the poor slope of the spline near
% time 2. And examine your homework solutions.
% compare the __maximum_ deviations
errLinearPlot=max(abs(TempLinearPlot-TempExactPlot))
errSplinePlot=max(abs(TempSplinePlot-TempExactPlot))
disp('There is no longer a real difference in error.')
% The maximum deviations are practically speaking the
% same. There is no longer a good reason to use spline
% interpolation instead of the simpler linear
% interpolation.
disp(' ')
```

```
time = 0.70000
TempExact = 6.7600
TempLinear = 6.8000
TempSpline = 6.5300
Now the linear interpolation is actually better!
errLinear = 0.040009
errSpline = 0.22999
errLinearPlot = 0.52550
errSplinePlot = 0.44453
There is no longer a real difference in error.
```


## SAVING AND RELOADING

You can save all work space variables in a file lecture4.mat using the

```
save lecture4
```

command. Then next time, you can resume where you left off using the

```
load lecture4
```

command.
Some things you may want to remember for future use: First, to save only a few variables, you could use the save FILENAME VAR1 VAR2 ... command.
Second, to read in data from an Excel spreadsheet, use the xlsread command. To write data to an Excel sheet, use writetable or xlswrite. Use "cell arrays" if not all data is numerical.

```
% see what variables are defined
%who
% save them all in file lecture&.mat
```



```
%save lecture4
% let's test it works OK
% kill all variables in the work space
%clear
% check that they are gone (no response)
%who
% reload the variables from file lecture4.mat
%load lecture4
% check that they are back.
%who
```


## CURVE FITTING

Functions interp1 and spline reproduce the given measured data exactly. This was fine when the measured data were exact. However, the noisy measured data we are looking at now have errors. Functions interp1 and spline will reproduce these errors exactly too. And that is bad news because of course we do not want these errors.

So if we want something more accurate than interp1 and spline, we must drop the assumption that our interpolation reproduces all the measured data exactly. The interpolation we want should be close to the measured data, but it should not swing around wildly to go exactly through each measured point.
To prevent our interpolation from wildly swinging around, what we can do choose a relatively simple curve type. Then we can adjust that curve type to be on average as close as possible to the data points. This idea is called "curve fitting".
In particular, recall that the exact temperature curve is given by

$$
T_{\text {exact }}=14.6 \exp (-1.1 t) ;
$$

However, we are assuming that we do not know that. And given only our noisy data, there is no way to figure out that the above is the exact temperature.
But suppose that we can guess (based on theoretical arguments not of importance here) that the desired temperature is of the form

$$
T=A \exp (B t)
$$

Using that as the interpolating function, there is no possibility of wildly swinging about. And we can still choose values for the constants $A$ and $B$ that produce the best approximation to the measured data. This is sure to produce a better result than interp1 and spline.
Of course, the devil is in the details. In particular, how are you going to find the best $A$ and $B$ ? You could select $A$ and $B$ to make the curve go exactly through two 2 of the 5 measured temperatures. But which 2? If you are very lucky you could get a quite good approximation that way. But if you are unlucky, you would get unnecessarily big errors.
It is a much better idea to use all 5 measured data you have, and make the curve approximate them on average as well as it can. Typically, numerical analysist take "on average" to mean that they make the average square error as small as possible. There are both theoretical and practical reasons to do that:

1. Theoretically, in simple cases where the errors are truly random, this gives the best approximation possible (according to mathematical statistics).
2. Practically, the mathematics of making the average square error as small as possible is a lot simpler than other possibilities (like making the maximum error as small as possible).

We do not really need to worry about the latter anyway, as Matlab does that work for us. What we should get away with is that what we are going to do is popularly known as the "Method of Least Squares". (Though "Method of Least Average Square Error" would be more accurate.)

## Fitting a line

Finding the best exponential approximation of the form

$$
T=A \exp (B t)
$$

is actually somewhat messy.
So, for now, we will restrict ourself to simpler approximations. And the simplest approximation possible is surely by a straight line,

$$
T=C_{1} t+C_{2}
$$

(call it TempLinFit in Matlab).
If we settle for that as the interpolating function, Matlab can help us by finding the "best" (in the least square sense) values for the coefficients $C_{1}$ and $C_{2}$ for us. All we need to do is use a function called polyfit (for "fit a polynomial") on the measured data. (Note that the straight line relationship above is a polynomial of degree 1 , since the highest power of x is 1.)
And having found the coefficients $C_{1}$ and $C_{2}$ of the polynomial with polyfit, we can use another Matlab function, polyval (for "find values of a polynomial"), to evaluate the polynomial at whatever times we want.
Note some more important terminology that you will frequently encounter in interpolation. In particular, the expression for $T$ above is linear in the coefficients $C_{1}$ and $C_{2}$ to find. That is unlike for the exponential fit, where the coefficient $B$ was inside an exponential, and that was then multiplied by $A$ to boot. If the approximate expression is linear in terms of the unknown coefficients, like the straight line above, numerical analysists speak of "linear regression". Like "method of least squares", "linear regression" is another term you should try to remember.

```
% find the coefficients C1 and C2 of the fitted line
n=1;
CoefLinFit=polyfit(timeMeasured, TempMeasured,n)
% interpolate again at t=0.7
time=0.7
TempExact=TempExactFun(time)
TempLinFit=polyval(CoefLinFit, time)
errLinFit=abs(TempLinFit-TempExact)
disp('OOPS! That is horrible!')
% let's see the linear fit in a plot
TempLinFitPlot=polyval(CoefLinFit, timePlot);
plot(timePlot,TempExactPlot, '--k',...
    timeMeasured,TempMeasured, 'ok', ...
    timePlot, TempLinFitPlot, 'y')
legend('Exact', 'Measured', 'Linear fit')
title('Least-Square Approximation with a Line')
```

```
xlabel('t (minutes)')
ylabel('T (Centigrade)')
% print the error
errLinFitPlot=max(abs(TempLinFitPlot-TempExactPlot))
disp('That is horrible, but what do you expect?')
disp('Clearly no straight line could approximate')
disp('the exact curve in this example well.')
disp(',')
```

CoefLinFit $=$ $-6.2000 \quad 12.8000$
time $=0.70000$
TempExact $=6.7600$
TempLinFit $=8.4600$
errLinFit $=1.7000$
OOPS! That is horrible!
errLinFitPlot $=1.8000$
That is horrible, but what do you expect?
Clearly no straight line could approximate the exact curve in this example well.


## Fitting a parabola

We can improve things quite a lot by approximating with a quadratic polynomial, i.e. a parabola,

$$
T=C_{1} t^{2}+C_{2} t+C_{3}
$$

instead of a straight line.
We will call this TempParFit (parabolic Temperature fit) in Matlab.

```
% find coefficients C1, C2, and C3
n=2;
CoefParFit=polyfit(timeMeasured, TempMeasured,n)
% interpolate again at t=0.7
time=0.7
TempExact=TempExactFun(time)
TempParFit=polyval(CoefParFit, time)
disp('That is much better than the linear fit.')
% let's see the quadratic fit in a plot
TempParFitPlot=polyval(CoefParFit, timePlot);
plot(timePlot,TempExactPlot,'--k',
    timeMeasured,TempMeasured, 'ok', ...
    timePlot, TempParFitPlot, 'm')
legend('Exact','Measured','Quadratic fit')
title('Least-Square Approximation with a Parabola')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
disp('Not too bad.')
% print the error
errParFitPlot=max(abs(TempParFitPlot-TempExactPlot))
disp('But the maximum error, at t=2, is quite big.')
disp(',')
```

```
    CoefParFit =
        3.7143 -13.6286 14.6571
    time = 0.70000
    TempExact = 6.7600
    TempParFit = 6.9371
    That is much better than the linear fit.
    Not too bad.
    errParFitPlot = 0.63942
    But the maximum error, at t=2, is quite big.
```



## Fitting a quartic

Let's try fitting with a quartic,

$$
T=C_{1} t^{4}+C_{2} t^{3}+C_{3} t^{2}+C_{4} t+C_{5}
$$

Note however, that now we are no longer fitting, but interpolating. With 5 unknown coefficients, the quartic can go through all 5 measured data points. This is usually a very bad idea.
In this particular case, the results below are much better than I expected. Fitting curves with too many coefficients can give very bad results. In this case the only real problem is the slope at $t=2$. It might have been much worse.

```
The general rule of thumb is:
    Do not interpolate a polynomial of degree more than
    about the square root of the number of data points
```

Since we have 5 data points and $\operatorname{sqrt}(5)$ is about 2, we should not fit a polynomial of a degree greater than 2 .
Exceptions confirm the rule.

```
% find the 5 coefficients
n=4;
CoefQuartFit=polyfit(timeMeasured,TempMeasured,n)
```

```
% interpolate again at t=0.7
time=0.7
TempExact=TempExactFun(time)
TempQuartFit=polyval(CoefQuartFit,time)
errQuartFit=abs(TempQuartFit-TempExact)
% let's see the quartic fit in a plot
TempQuartFitPlot=polyval(CoefQuartFit, timePlot);
plot(timePlot,TempExactPlot,'--k',...
    timeMeasured,TempMeasured, 'ok',,..
    timePlot,TempQuartFitPlot,'c')
legend('Exact','Measured','Quartic fit')
title('Least-Square Approximation with a Quartic')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
% print the error
errQuartFitPlot=max(abs(TempQuartFitPlot-TempExactPlot))
disp(' ')
```

```
CoefQuartFit =
        2.0000 -10.0000 19.5000 -21.5000 15.0000
time = 0.70000
TempExact = 6.7600
TempQuartFit = 6.5552
errQuartFit = 0.20479
errQuartFitPlot = 0.47325
```


## Extrapolation again

We already saw that extrapolation, i.e. evaluating outside the given range is fraught with peril. Let's try the fitted polynomials now.

```
% extrapolate again at t=5
time=5
TempExact=TempExactFun(time)
TempLinear=interp1(timeMeasured,TempMeasured, time,...
    'linear', 'extrap')
TempSpline=spline(timeMeasured,TempMeasured, time)
TempParFit=polyval(CoefParFit, time)
TempQuartFit=polyval(CoefQuartFit, time)
disp('Obviously, the extrapolated results are no good.')
disp (', ')
```

```
time = 5
```



TempExact $=0.059667$
TempLinear $=-4$
TempSpline $=59$
TempParFit $=39.371$
TempQuartFit $=395.00$
Obviously, the extrapolated results are no good.

## SKIP: Fitting an exponential

According to the above, fitting a polynomial of at least quadratic degree worked reaonably well. But as noted earlier, it should be a much better idea to fit an exponential of the form

$$
T=A \exp (B t)
$$

to our five data points. The reason is that the exact temperature is of the form above. You only need to get $A(14.6)$ and $B(-1.1)$ right, and you will get the right temperature, even in extrapolation.
The reason we did so far not try this is because the above expression is nonlinear in $A$ and $B$. Then Matlab's polyfit function does not work.
However, we can apply a trick. If we take a natural logarithm of the expression above, we get:

$$
\ln (T)=\ln (A)+B t
$$

Defining new variables as

$$
C_{1}=B \quad C_{2}=\ln (A)
$$

this takes the form

$$
\ln (T)=C_{1} t+C_{2}
$$

That is just fitting by a straight line, but for $\ln (T)$ instead of $T$ ! The latter is not a problem; when we have $T$, we can find $\ln (T)$ by just taking a logarithm. And when we have $\ln (T)$, we can find $T$ by just taking an exponential. Below we try this out. Note that Matlab uses $\log$ for $\ln ($ and $\log 10$ for $\log$ ).

```
% create the measured ln (T) values
lnTempMeasured=log(TempMeasured);
% find C1 and C2
n=1;
CoefExpFit=polyfit(timeMeasured, lnTempMeasured,n)
% interpolate again at t=0.7
time=0.7
% note the exp to convert ln(T) to T
TempExpFit=exp(polyval(CoefExpFit, time))
TempExact=TempExactFun(time)
% let's see the exponential fit in a plot
TempExpFitPlot=exp(polyval(CoefExpFit,timePlot));
plot(timePlot,TempExactPlot, ':k',...
    timeMeasured,TempMeasured, 'om' ,...
    timePlot, TempExpFitPlot, 'g')
legend('Exact','Measured','Exponential fit')
title('Exponential least-square approximation')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
errExpFitPlot=max(abs(TempExpFitPlot-TempExactPlot))
disp('A bit disappointing, maybe.')
disp(', ')
% extrapolate again at t=5
time=5
TempExact=TempExactFun(time)
TempExpFit=exp(polyval(CoefExpFit, time))
disp(',')
```

```
CoefExpFit =
    -1.0021 2.6399
time=0.70000
TempExpFit = 6.9475
TempExact = 6.7600
errExpFitPlot = 0.58869
A bit disappointing, maybe.
time = 5
TempExact = 0.059667
TempExpFit = 0.093409
```



## SKIP: More on the exponential fit

The reason that the maximum error in the exponential fit is not much better than the quadratic one has to do with our manipulations. Since we changed unknowns to $\ln (T)$, Matlab is no longer making the average error in $T$ as small as possible. It is now making the average error in $\ln (T)$ as small as possible. This can be good or bad, depending on conditions. The error in $T$ is the "absolute" error in the temperature. The error in $\ln (T)$ is the "relative" error in the temperature; the error relative to the magnitude of $T$. In other words,
the error in $\ln (T)$ gives the percentage error in $T$. Sometimes you would rather have the relative error as small as possible, instead of the absolute error.
On the other hand, if we are really interested in getting the smallest absolute error, there is a trick. Note first that the intial temperature is about 6 times bigger than the final temperature. To force Matlab to give more attention to that larger value, we can put it inside the measured data lists 6 times. Similarly, the value at $t=0.5$ is about 3 times the final value and the one at $t=1$ about 2 times, So we place these data that many times in the measured data lists.
Another way to achieve a similar effect would be to concentrate the measurements near the start, where the temperature is largest. But we will assume that the available measurements are as given.

```
% let's check relative errors (note the ./)
RelErrParFit=max(...
    abs(TempParFitPlot-TempExactPlot)./ TempExactPlot)
RelErrExpFit=max(...
    abs(TempExpFitPlot-TempExactPlot)./ TempExactPlot)
disp('The relative error is much better!')
% lets improve the absolute error using the trick now
timeMeasuredMod = ...
        [ [\begin{array}{lllllllllllllllll}{0}&{0}&{0}&{0}&{0}&{0}&{0.5}&{0.5}&{0.5}&{1}&{1}&{1.5}&{2}\end{array}]}\mp@subsup{}{}{\prime}
TempMeasuredMod = ...
        [15
lnTempMeasuredMod=log}(\mathrm{ TempMeasuredMod);
n=1;
CoefExpFitMod=...
        polyfit(timeMeasuredMod, lnTempMeasuredMod,n)
% interpolate again at t=0.7
time=0.7
TempExpFitMod=exp(polyval(CoefExpFitMod,time))
TempExact=TempExactFun(time)
% compare the interpolations in a plot
TempExpFitModPlot=exp(polyval(CoefExpFitMod,timePlot));
plot(timePlot,TempExactPlot, ,'k', ...
    timeMeasured,TempMeasured, 'om' ,...
    timePlot, TempExpFitModPlot, 'c')
legend('Exact','Measured','Modified exponential fit')
title('Modified exponential least-square approximation')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
disp('Not too bad.')
disp(',')
```

```
% compare the __maximum_ deviations
errExpFitModPlot=...
    max(abs(TempExpFitModPlot-TempExactPlot))
disp('The error is now much smaller than anything seen')
disp('before. And we also follow the slope of the')
disp('exact curve very well.')
disp(', )
% extrapolate again at t=5
time=5
TempExact=TempExactFun(time)
TempExpFit=exp(polyval(CoefExpFit, time))
TempExpFitMod=exp(polyval(CoefExpFitMod,time))
disp('Not too bad.')
disp(',')
```

```
RelErrParFit = 0.39526
RelErrExpFit = 0.16718
The relative error is much better!
CoefExpFitMod =
    -1.0388 2.6746
time=0.70000
TempExpFitMod = 7.0102
TempExact = 6.7600
Not too bad.
errExpFitModPlot = 0.27342
The error is now much smaller than anything seen
before. And we also follow the slope of the
exact curve very well.
time = 5
TempExact = 0.059667
TempExpFit = 0.093409
TempExpFitMod = 0.080485
Not too bad.
```


## MORE MEASUREMENTS

If we would measure a lot more points than the 5 we have, and the errors in these measurements would be random, we could get a much better approximation. Unfortunately, rounding of temperatures to whole degrees is not random. It creates a deterministic "staircase" of numbers. But we can try anyway.
Note: We will cheat, and use the exact solution, which we are not supposed to know, to avoid doing and typing in 41 measurements.


```
% create the new 41 "measured" data
timeMeasured 2=linspace (0,2,41);
% 'round' rounds to whole numbers
TempMeasured2=round(TempExactFun(timeMeasured2));
% use some more plot points now too
timePlot2=linspace ( 0, 2,300);
TempExactPlot2=TempExactFun(timePlot2);
disp(' ')
```


## Interpolation with more data

Note that the interpolations do not improve if we use more noisy points.

```
% compare the interpolations in a plot
TempLinearPlot2 =...
    interp1(timeMeasured2,TempMeasured2, timePlot2);
TempSplinePlot2=...
    spline(timeMeasured2,TempMeasured2,timePlot2);
plot(timePlot2,TempExactPlot2,'--k', ...
    timeMeasured2,TempMeasured2, 'ok', ...
```

```
    timePlot2,TempLinearPlot2, 'r', ...
    timePlot2,TempSplinePlot2, 'b')
legend('Exact','Measured ','Linear', 'Spline')
title('Linear and Spline Interpolation')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
disp('Seems worse than before.')
disp(', ')
% compare the __maximum_ deviations
errLinearPlot
errLinearPlot 2=max( abs(TempLinearPlot2-TempExactPlot2))
errSplinePlot
errSplinePlot2=\boldsymbol{max}(\mathbf{abs}(TempSplinePlot2-TempExactPlot2))
disp('Now the spline is worse that linear!')
disp(',')
```

Seems worse than before.

```
errLinearPlot = 0.52550
errLinearPlot2 = 0.48471
errSplinePlot = 0.44453
errSplinePlot2 = 0.55055
Now the spline is worse that linear!
```


## Quartic fit with more data

```
% repeat the quartic fit
n=4;
CoefQuartFit2=polyfit(timeMeasured2,TempMeasured2,n)
% compare the interpolations in a plot
TempQuartFitPlot2=polyval(CoefQuartFit2,timePlot2);
plot(timePlot2,TempExactPlot2, '--k',...
    timeMeasured2,TempMeasured2,'ok',},
    timePlot2,TempQuartFitPlot2, 'c')
legend('Exact','Measured','Quartic fit')
title('Least-Square Approximation with a Quartic')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
disp('Over most of the range, this is much better than')
disp('the result for 5 measured values (which went')
disp('through all measured points).')
disp (', ')
```



```
% compare the __maximum_ deviations
errQuartFitPlot
errQuartFitPlot2=...
    max(abs(TempQuartFitPlot2-TempExactPlot2))
disp('The disappointing maximum error is due to the')
disp('fact that the final "measured" points are all too')
disp('high. Have a good look at the end of the graph!')
disp(', ')
```

CoefQuartFit2 =

$$
\begin{array}{lllll}
1.2249 & -6.0707 & 13.1791 & -18.2949 & 14.8320
\end{array}
$$

Over most of the range, this is much better than the result for 5 measured values (which went through all measured points).
errQuartFitPlot $=0.47325$
errQuartFitPlot2 $=0.37455$
The disappointing maximum error is due to the fact that the final "measured" points are all too high. Have a good look at the end of the graph!


## SKIP: Exponential fit with more data

```
% repeat the exponential fit
lnTempMeasured2=\boldsymbol{log}(TempMeasured2);
n=1;
CoefExpFit2=polyfit(timeMeasured2, lnTempMeasured2,n)
% compare the interpolations in a plot
TempExpFitPlot2=exp(polyval(CoefExpFit2,timePlot2));
plot(timePlot2,TempExactPlot2,',:k',...
    timeMeasured2,TempMeasured2, 'ok', ,..
    timePlot2,TempExpFitPlot2,'g')
legend('Exact','Measured','Exponential fit')
title('Least-Square Approximation with an Exponential')
xlabel('t (minutes)')
ylabel('T (Centigrade)')
disp(',}
% compare the __maximum_ deviations
errExpFitPlot
errExpFitPlot2=\boldsymbol{max}(\mathbf{abs}(TempExpFitPlot2-TempExactPlot2))
disp('Clearly, that is quite good.')
```

```
CoefExpFit2 =
    -1.0704 2.6558
errExpFitPlot = 0.58869
errExpFitPlot2 = 0.36353
Clearly, that is quite good.
```



## INTEGRALS

It is easy to do determined integrals, with given limits, using Matlab. Just use the integral function. (Octave still uses the old name quad.)
As an example (which you do not actually have to understand), suppose we want to know how much radiation $q$ the bar in our example emits per unit surface area while cooling down. Assuming that the bar surface is perfectly black, the Stefan-Boltzmann law says that the radiation emitted per unit area and unit time is given by

$$
\dot{q}=\sigma T^{4} \quad \sigma=5.67037310^{-8} \mathrm{~W} / \mathrm{m}^{2} \mathrm{~K}^{4}
$$

where $T$ is the absolute temperature in K (Kelvin) and $\sigma$ is called the "StefanBoltzmann constant." To get the $q$ we want, we need to integrate $\dot{q}$ above from time 0 to time 2 :

$$
q=\int_{0}^{2} \sigma T^{4} \mathrm{~d} t
$$

If you do not understand why, that is OK. All you need to know is that

1. We want to do the integral above.
2. Since $T$ above is in K, we must add $T_{0}=273.15$ to our temperatures, which are in Centigrade. Also we need to insert a factor 60 to convert our times from minutes to seconds.
3. In Matlab integration is nowadays done by a function called integral. Octave still uses the old name quad.
4. Function integral (or quad) can only integrate functions. You cannot use it to integrate measured data or plot points! (There are different methods to do that, like "spline integration", but we do not cover those here.)
```
% the Stefan-Boltzmann constant in W/m^2 K^4:
sigma=5.670373E-8;
% 0 degrees Centigrade in Kelvin
T0=273.15;
```


## The exact integral

Let's find the exact integral first using our knowledge of Calculus I. To integrate

$$
q=\int_{0}^{2} \sigma\left(A \exp (B t)+T_{0}\right)^{4} \mathrm{~d} t \quad A=14.6, B=-1.1
$$

with respect to time, change integration variable to $u=A \exp (B t)$ and take it from there.

```
% names for the constants in TempExact = A exp(B t)
A=14.6;
B=-1.1;
% evaluate the start (t=0) and end (t=2) values of u
u1=A;
u2=A*\operatorname{exp}(B*2);
% evaluate the integral as found by calculus
```

```
qTrue=60*sigma * (...
    1/4*(u2^4-u1^4)+\ldots
    4/3*T0*(u2^3-u1^3)+...
    3*T0^2*(u2^2-u1^2) +...
    4*T0^ 3*(u2-u1) +...
    T0^4*(log(u2)-log}(\textrm{u}1)))/\textrm{B}
fprintf('Truly exact: %.3f\n', qTrue)
```

Truly exact: 41301.515

## Numerical integrations

Next let's use numerical integration, i.e. integral or quad, to find the integral. Note that there will be an error created by the numerical integration, even if we integrate the exact temperature.
We already noted before that integral or quad can only integrate a function. So typically, we will provide it an anonymous function of the time $t$, in

## @ ( t ) FUNCTION (..., t , ...)

notation, where t is the time and dots stand for other parameters of FUNCTION. Matlab functions that can be used to create FUNCTION are TempExactFun, interp1, spline, and polyval (after their other parameters have been found). Do not try to put in arrays (like ...Measured or ...Plot) except as parameters of these functions!
Note that all obtained values below will be pretty accurate:

```
Typically:
    Numerical errors tend to become less in integrals.
```

```
% try numerical integration of the exact temperature
```

% try numerical integration of the exact temperature
qExact = 60*sigma*quad ( . .
qExact = 60*sigma*quad ( . .
@(t) (TempExactFun(t)+T0).^ 4,0,2);
@(t) (TempExactFun(t)+T0).^ 4,0,2);
fprintf('Numerical integration: %.3f Error: %.1E%%\n',...
fprintf('Numerical integration: %.3f Error: %.1E%%\n',...
qExact, abs(qExact-qTrue)/qTrue*100)
qExact, abs(qExact-qTrue)/qTrue*100)
disp('As shown, numerical integration for a smooth')
disp('As shown, numerical integration for a smooth')
disp('function like this will be very accurate.')
disp('function like this will be very accurate.')
disp('The error is smaller than the round-off.')
disp('The error is smaller than the round-off.')
% try numerical integration of the linear interpolation
% try numerical integration of the linear interpolation
qLinear = 60*sigma *quad ( . .
qLinear = 60*sigma *quad ( . .
@(t) (interp1(timeMeasured, TempMeasured, t )+T0).^4,0,2);
@(t) (interp1(timeMeasured, TempMeasured, t )+T0).^4,0,2);
fprintf('Linear interpolation: %.3f Error: %.3f%%\n',...
fprintf('Linear interpolation: %.3f Error: %.3f%%\n',...
qLinear, abs(qLinear-qTrue)/qTrue*100)
qLinear, abs(qLinear-qTrue)/qTrue*100)
% try numerical integration of the spline interpolation

```
% try numerical integration of the spline interpolation
```

```
qSpline=60*sigma*quad (...
    @(t) (spline(timeMeasured,TempMeasured,t)+T0).^4,0,2);
fprintf('Spline interpolation: %.3f Error: %.3f%%\n',...
    qSpline,abs(qSpline-qTrue)/qTrue*100)
% try numerical integration of the parabolic fit
qParFit=60*sigma*quad ( . . 
    @(t) (polyval(CoefParFit,t)+T0).^4,0,2);
fprintf('Parabolic Fit: %.3f Error: %.3f%%\n',...
    qParFit,abs(qParFit-qTrue)/qTrue*100)
% try numerical integration of the quartic fit
qQuartFit=60*sigma*quad (...
    @(t) (polyval(CoefQuartFit, t)+T0).^4,0,2);
fprintf('Quartic Fit: %.3f Error: %.3f%%\n',...
    qQuartFit,abs(qQuartFit-qTrue)/qTrue*100)
disp(',')
```

Numerical integration: 41301.515 Error: $0.0 \mathrm{E}+00 \%$
As shown, numerical integration for a smooth
function like this will be very accurate.
The error is smaller than the round-off.
Linear interpolation: 41434.104 Error: $0.321 \%$
Spline interpolation: 41307.239 Error: $0.014 \%$
Parabolic Fit: 41352.074 Error: $0.122 \%$
Quartic Fit: $\quad 41297.198$ Error: $0.010 \%$

## SKIP: More on integration

In this section we will show how the exponential curve fits work out. We will also show how you can integrate the polynomial fits exactly if you want. Not only does this eliminate all integration errors, however small, Matlab can also do it much more quickly. That could be important if you have to do a lot of these integrals. The trick is to use function polyint instead of integral or quad to do the integration.

```
% try numerical integration of the exponential fit
B=CoefExpFit(1);
lnA=CoefExpFit (2);
qExpFit=quad(@(t) (exp(B*t+lnA )+T0).^ 4,0,2) *60*sigma ;
fprintf('Exponential Fit: %.3f Error: %.3f%%\n',...
    qExpFit,abs(qExpFit-qTrue)/qTrue*100)
% try numerical integration of the tricked one too
B=CoefExpFitMod (1);
lnA=CoefExpFitMod (2);
```

```
qExpFitMod=quad(@(t) (exp(B*t+lnA )+T0).^ 4,0,2)*60*\operatorname{sigma};
fprintf('Exponential Fit, Mod: %.3f Error: %.3f%%\n',...
    qExpFitMod,abs(qExpFitMod-qTrue)/qTrue*100)
% integrate the parabolic fit exactly now
disp('Exact integration of the parabolic fit:')
% first convert the polynomial to Kelvin by adding TO
tempC=CoefParFit;
tempC}(\mathrm{ end )}=\operatorname{tempC}(\mathrm{ end )}+\textrm{T}0
% now square that polynomial twice to get T^4
tempC=\boldsymbol{conv}(tempC, tempC);
tempC=conv (tempC, tempC);
% find the antiderivative polynomial using polyint
tempC=polyint(tempC);
% evaluate the integral between 0 and 2 with that
tempInt=polyval(tempC,2)-polyval(tempC,0);
% add the remaining factors
qParExact=tempInt*60*sigma;
fprintf('Quadratic Fit, exact: %.3f Error: %.3f%%\n',,..
    qParExact, abs(qParExact-qTrue)/qTrue*100)
% integrate the quartic fit the same way
disp('Exact integration of the quartic fit:')
% first convert the polynomial to Kelvin by adding T0
tempC=CoefQuartFit;
tempC}(\mathrm{ end })=\operatorname{tempC}(\mathrm{ end })+\textrm{T}0
% now square that polynomial twice to get T^4
tempC=conv( tempC, tempC);
tempC=conv(tempC, tempC);
% find the antiderivative polynomial using polyint
tempC=polyint(tempC);
% evaluate the integral between 0 and 2 with that
tempInt=polyval(tempC,2)-polyval(tempC,0);
% add the remaining factors
qQuartExact=tempInt*60*sigma;
fprintf('Quartic Fit, exact: %.3f Error: %.3f%%\n',...
    qQuartExact,abs(qQuartExact-qTrue)/qTrue*100)
disp(', ')
```

Exponential Fit: $\quad 41384.031$ Error: $0.200 \%$
Exponential Fit, Mod: 41422.232 Error: $0.292 \%$
Exact integration of the parabolic fit:
Quadratic Fit, exact: 41352.074 Error: $0.122 \%$
Exact integration of the quartic fit:
Quartic Fit, exact: 41297.198 Error: $0.010 \%$

## DERIVATIVES

Sometimes we are interested in the derivative of the quantity in question. In the present example, it is a measure of how much heat leaks out of the bar per unit time.

## The exact derivative

Since

$$
T_{\text {exact }}=A \exp (B t) \quad A=14.6, B=-1.1
$$

its derivative is simply

$$
\frac{\mathrm{d} T_{\text {exact }}}{\mathrm{d} t}=B T_{\text {exact }} \quad B=-1.1
$$

(That follows from differentiating the exponential using the chain rule.)

```
% derivative of TempExact found analytically
derTempExactPlot=-1.1*TempExactPlot;
```


## Numerical differentiation

For the linear, quadratic, and quartic fits, we can use the fact that Matlab function polyder will find the coefficients of the derivative polynomial for us. Then we can use our old faithful polyval to evaluate that derivative polynomial. In this section we will use these methods to find the derivative of the temperature at our plot points, and then plot the results. We will compare the quadratic for 5 noisy measurements and the quartic for 41.
Note that the results will be pretty bad.

```
Typically:
    Errors tend to become much worse in derivatives.
```

We will also plot the quartic for 41 noisy data points when the noise is random, rather than due to a systematic rounding error. This will allow the method of least squares to work like it is designed for. The results will be much better.

```
% derivative of the parabolic fit polynomial
derCoefParFit=polyder(CoefParFit);
% use it to evaluate the derivative at the plot points
derTempParFitPlot=polyval(derCoefParFit,timePlot);
% derivative of the quartic fit polynomial, 41 points
derCoefQuartFit2=polyder(CoefQuartFit2);
% use it to evaluate the derivative at the plot points
derTempQuartFitPlot2=polyval(derCoefQuartFit2, timePlot2);
```

```
% quartic fit, 41 points with random errors
randn(" seed ",9);
TempMeasured3 = ...
    TempExactFun(timeMeasured2) +0.25*\boldsymbol{randn}(1,41);
n=4;
CoefQuartFit3=polyfit(timeMeasured2,TempMeasured3,n)
% derivative of the quartic fit polynomial, 41 points
derCoefQuartFit3=polyder(CoefQuartFit3);
% use it to evaluate the derivative at the plot points
derTempQuartFitPlot3=polyval(derCoefQuartFit3,timePlot2);
% plot it
plot(timePlot, derTempExactPlot,'--k',...
    timePlot, derTempParFitPlot, 'm',...
    timePlot2, derTempQuartFitPlot2, 'c',...
    timePlot2, derTempQuartFitPlot3,'g')
axis([[0 2 - 20 0}]
legend('Exact',...
    'Quadratic fit, 5 noisy data points',...
    'Quartic fit, 41 noisy data points',...
    'idem, but with *random* errors')
legend('location','southeast')
title('Comparison of Predicted First Derivatives')
xlabel('t (minutes)')
ylabel('dT/dt (Centigrade/min)')
disp('The polynomial fit derivatives are pretty bad.')
disp('The quartic is no better than the quadratic.')
disp('However, if the noise is really random, the')
disp('quartic can become quite good for a lot of')
disp('data points.')
disp(',')
```

CoefQuartFit3 =
$\begin{array}{lllll}0.48051 & -3.22981 & 9.56650 & -16.60748 & 14.70296\end{array}$
The polynomial fit derivatives are pretty bad.
The quartic is no better than the quadratic. However, if the noise is really random, the quartic can become quite good for a lot of data points.

## SKIP: More on differentiation

In this section we show the derivatives of the exponential fits obtained earlier. As expected, these are much more reasonable. Both the exponential fit for 41

noisy measurements, as well as the modified fit for 5 noisy measurements are plotted.
How about the derivative of your beloved interpolated spline? Well, linear and spline interpolation are described by "piecewise polynomials": there is a different polynomial in each segment between measured points. The bad thing is that the idiots at MathWorks never defined a function to find the derivatives of piecewise polynomials. If you want the derivative of your spline, look for 'ppder' or 'ppdiff' provided by third parties, (where pp is an acronym for "piecewise polynomial".) Octave provides ppder. This is used below to plot the derivative of the spline with 5 exact measurements (pretty good). It is also used to plot the derivative of the spline with 41 noisy measurements (very bad).

```
Remember:
    Spline differentiation might be good,
        but noisy data are a big problem.
```

Note added 9/22/2018: Matlab R2018b now seems to have fnder for derivatives (and fnint for integrals) of piecewise polynomials. Unfortunately, we are still using Matlab R2017b at the time of writing.

```
% derivatives of TempExpFit2
derTempExpFitPlot2=CoefExpFit2 (1)*TempExpFitPlot2;
% piecewise polynomial coefficients of the spline
```

```
ppSpline=spline(timeMeasured,TempExactFun(timeMeasured));
% find the coeeficients of the derivative
derppSpline=ppder(ppSpline);
% evaluate at the plot points
derTempSplinePlot=ppval(derppSpline,timePlot);
% piecewise polynomial coefficients of the spline
ppSpline2=spline(timeMeasured2,TempMeasured2);
% find the coeeficients of the derivative
derppSpline2=ppder(ppSpline2);
% evaluate at the plot points
derTempSplinePlot2=ppval(derppSpline2, timePlot2);
% plot it
plot(timePlot, derTempExactPlot, , :k',...
    timePlot2, derTempExpFitPlot2,'g',...
    timePlot, derTempSplinePlot, 'b',...
    timePlot2, derTempSplinePlot2, 'm')
axis([[0 2 - 20 0}|]
legend ('Exact',...
    'Exponential fit, 41 noisy data points',...
    'Spline, 5 exact data points',...
    'Spline, 41 noisy data points')
legend('location','southeast')
title('Comparison of predicted first derivative')
xlabel('t (minutes)')
ylabel('dT/dt (Centigrade/min)')
disp('The exponential fit derivative is reasonable.')
disp('The spline is good for exact data, but noisy')
disp('data can be a big problem.')
disp(',')
```

The exponential fit derivative is reasonable. The spline is good for exact data, but noisy data can be a big problem.

## End lesson 3



