

MATLAB

CS101 lec25

Fitting Data

Announcements

quiz: [quiz25](#) due on Tues 17/12

lab: One last one.....

hw: [hw12](#) due Fri 18/12

Paper Exam - MCQs + Short Questions +
Programming question

Objectives

- A. Fit polynomials to data, from linear to high-order.
- B. Understand limitations of high-order fit.
- C. Distinguish interpolation and fitting (regression).
- D. Employ spline-based or piecewise fitting.

MATLAB Review

Question

```
p = [ 1 2 3 4 ];
```

Which polynomial does `p` represent?

A $x + 2x^2 + 3x^3 + 4x^4$

B $4 + 3x + 2x^2 + x^3$

C $1 + 2x + 3x^2 + 4x^3$

D $4x + 3x^2 + 2x^3 + x^4$

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Question

```
p = [ 1 0 0 0 -1 ];  
x = polyval( p,5 );
```

What is the final value of `x`? (No calculator necessary!)

- A 624
- B 124
- C 3120
- D -724

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Regression or Curve Fitting

Interpolate

Given $n + 1$ (x,y) points,
find y -values at x -values which are not in your given (x, y)
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Many methods inside `interp1`

- 'linear'

- 'nearest'

- 'pchip'

Fitting Polynomials

Given $n + 1$ (x,y) points (or more), we can fit an n th order polynomial as a model. `polyfit(x,y,n)`

Why n th order is the highest order with $n + 1$ points?

Fitting Polynomials

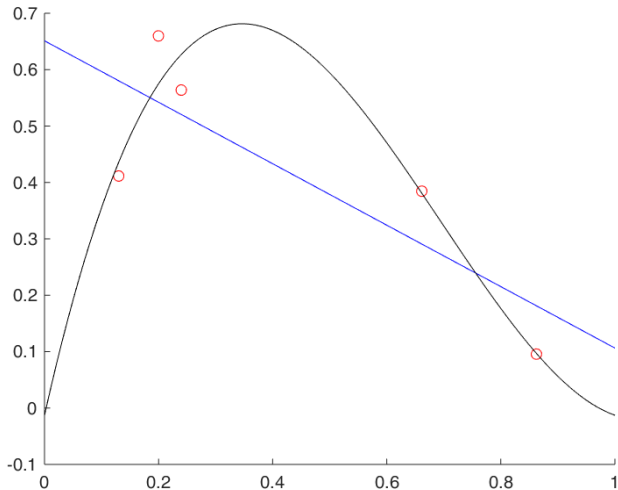
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Why n th order is the highest order with $n + 1$ points?

```
%generate our data
x = rand( 5,1 ); y = rand( 5,1 );
%generate our fit
xf = 0:0.01:1;
pf1 = polyfit( x,y,1 ); %linear
pf3 = polyfit( x,y,3 ); %cubic

%Plot our fit
yf1 = polyval( pf1,xf );
yf3 = polyval( pf3,xf );
hold on
plot( x,y,'ro', xf,yf1,'b-', xf,yf3,'k-' );
```

Fitting Polynomials



Fitting Polynomials

```
n = input( 'Give a polynomial order' );
x = rand( n+1,1 );
y = rand( n+1,1 );

xf = 0:0.01:1;
n1 = n % what polynomial order you want to fit
pf = polyfit( x,y,n1 );
yf = polyval( pf,xf );
plot( x,y,'rx', xf,yf,'r-' );
```


Fitting Polynomials

```
n = input( 'Give a polynomial order' );  
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```

```
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yf = polyval( pf,xf );  
plot( x,y,'rx', xf,yf,'r-' );
```

If $n_1 > n$, MATLAB gives *Warning: Polynomial is not unique; degree \geq number of data points. Why?*

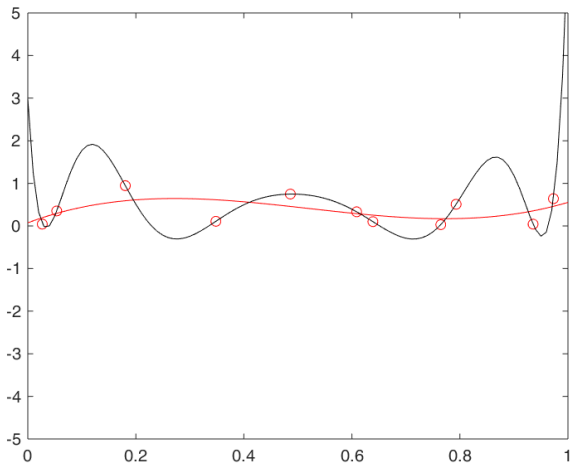
Fitting Polynomials

High-order polynomials tend to wobble a lot, and overshoot at the ends.

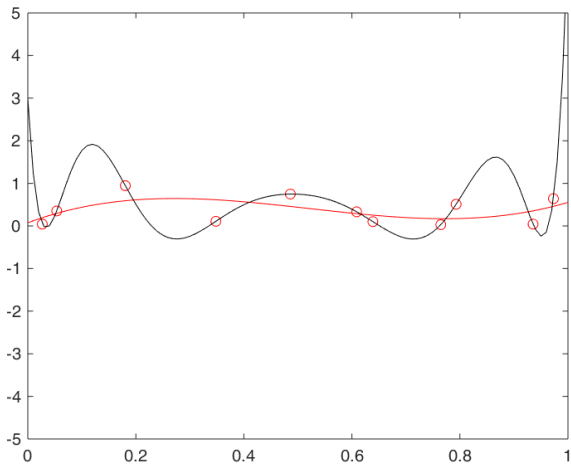
A simpler fit is often better!

```
x = rand( 11,1 );
y = rand( 11,1 );
xf = 0:0.01:1;
pf3  = polyfit( x,y,3 );
pf10 = polyfit( x,y,10 );
figure;
plot( x,y,'rx',xf,polyval( pf3,xf ),'r-',
      xf,polyval( pf10,xf ),'g-' );
ylim( [ -5 5 ] );
```

Fitting Polynomials

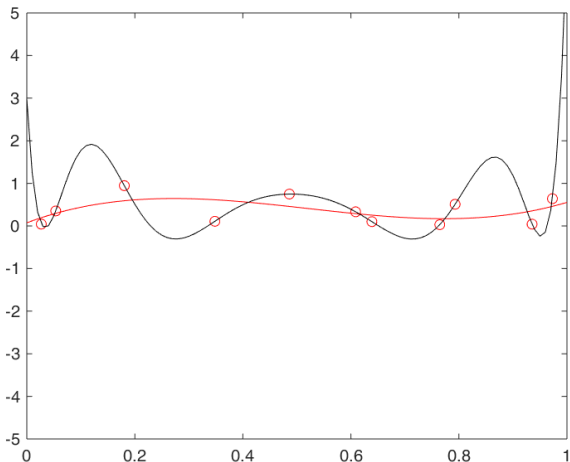


Fitting Polynomials



Which one looks better?

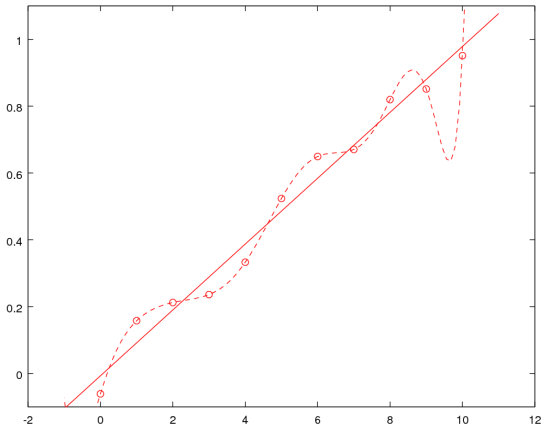
Fitting Polynomials



Which one looks better? Which one do you think is more real?

Overfitting

Insisting on too much precision can cause major problems!
Lower-order polynomial fits are best.



Error from Fitting

We would like to estimate the error of a fit.

Traditionally, this is the L^2 metric:

$$L^2 = |y_{\text{known}} - y_{\text{fitted}}|^2$$

This is always positive and should be close to zero.

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The quantity $y_{\text{known}} - y_{\text{fitted}}$ is the *residual*.

We may also want to know estimated error at any point (along the entire curve).

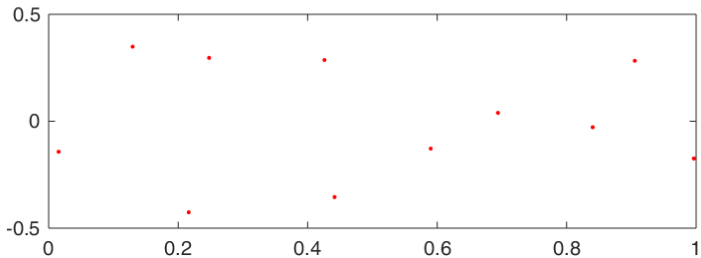
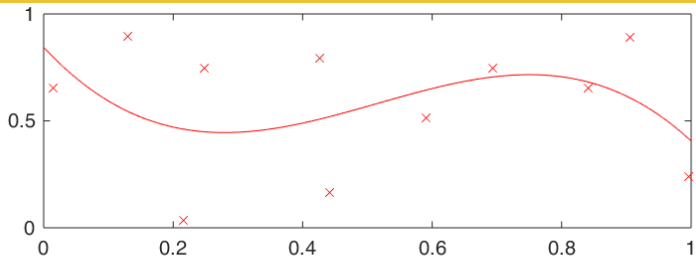
Error from Fitting

```
x = rand( 11,1 );
y = rand( 11,1 );

xf = 0:0.01:1;
pf  = polyfit( x,y,3 );
resids = y - polyval( pf,x )

figure;
subplot( 2,1,1 );
ylim( [ 0 1 ] );
plot( x,y,'rx',xf,polyval( pf3,xf ),'r-' );
subplot( 2,1,2 );
plot( x,resids,'r.' );
```

Fitting Polynomials



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(The quantity $y_{\text{known}} - y_{\text{fitted}}$ is the *residual*.)

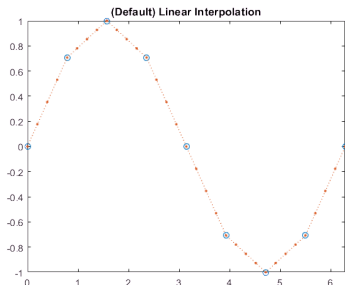
We may also want to know estimated error at any point (along the entire curve).

A good fit has a small residual (but the absolute size is contextual).

Linear interpolation

A related process, *interpolation* means estimating intermediate values (between two known points).

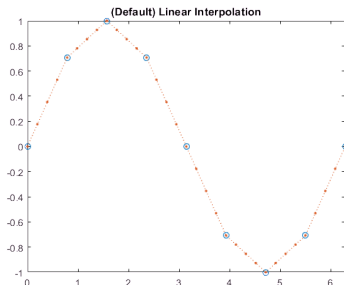
Be careful to distinguish this from a linear fit (regression).



Linear interpolation

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$$y = y_0 + (x - x_0) \frac{y_1 - y_0}{x_1 - x_0} = \frac{y_0(x_1 - x) + y_1(x - x_0)}{x_1 - x_0}$$

Linear interpolation vs Fitting 1

Plot to see to see the difference

```
% Sample
x_samples = linspace( 0,1,11 );
y_samples = ( x_samples - 0.5 ) .^ 2 + 0.01
            * randn( size( x_samples ) );

hold on
plot( x_samples,y_samples,'ro' );
```

Linear interpolation vs Fitting 2

```
% interpolation
x_span = linspace( 0,1,111 );
y_interp = interp1( x_samples,y_samples,x_span );
plot( x_span,y_interp,'b-' )

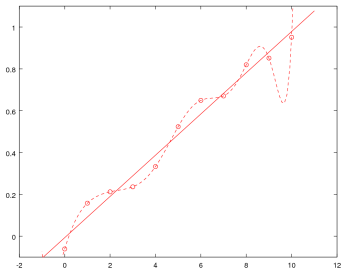
% polyfit
coefs = polyfit( x_samples,y_samples,2 );
y_regression = coefs(1)*x_span.^2 +
               coefs(2)*x_span + coefs(3);
plot( x_span,y_regression,'g-' )
```

Extrapolation

Modeling outside of the domain of reliable data is fraught with difficulty.

Consider the behavior outside of the domain here for either curve.

Unless you have a very good theoretical reason, *don't!*



Spline interpolation

Splines are piecewise polynomials designed to smoothly fit long segments without too much overfitting.

Splines are typically constructed from cubic polynomials.

Similar to 'pchip' in `interp1` but the results are different!

```
y_est = spline(x,y,x_est)
```

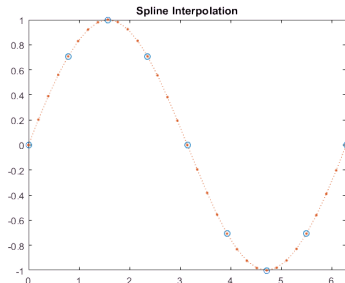
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```



2D Interpolation - Optional

In 2D, use `interp2` to get a single point, or `griddata` to reconstruct a whole grid:

Ex 1

```
x = 0:0.05:1;
y = 0:0.05:1;
z = rand( 21 );
xstar = 0.33;
ystar = 0.33;
zstar = interp2( x,y,z,xstar,ystar );

figure
hold on
mesh( x,y,z )
plot3( xstar,ystar,zstar,'o' )
```

2D Interpolation - Optional

Ex 2

```
f = @( x,y ) x.*( 1-x ).*cos( 4*pi*x ) ...  
        .* sin( 2*pi*sqrt( y ) );  
  
% Define the basic grid coordinates.  
grid_x = 0:0.01:1;  
grid_y = grid_x( 1,: );  
  
% Define a random subset of the grid for which  
% we will generate data.  
pts = rand( 800,2 ); % x,y pairs  
vals = f( pts( :,1 ),pts( :,2) );
```

2D Interpolation - Optional

Ex 2

```
% Generate a grid. 'nearest','linear','cubic'  
[ X Y ] = meshgrid( grid_x,grid_y );  
Z = griddata( pts( :,1 ),pts( :,2 ),vals, ...  
             X,Y,'linear' );  
  
hold on  
mesh( X,Y,Z )  
plot3( pts( :,1 ),pts( :,2 ),f(pts(:,1),...  
    pts(:,2)),'r.' )
```

Demo?

Summary

- A. `polyfit(x, y, n)`
- B. Interpolation vs Regression or Fitting
- C. Problems of fitting to higher power polynomials
- D. `spline(x, y, x-est)`