
Table of Contents

House Keeping	1
Part 1:	1
Part 2 (Create testing data):	2
Extra credit	3
Interpretation	4
Plotting	6
Functions	9

House Keeping

```
close all; clear all; clc;

%{
    CSCI 3656 HW9 main script
    Author: Connor O'Reilly
    email: coor1752 @colorado.edu
    Last Edited: 11/7/2021
%}
```

Part 1:

```
%define function
f = @(x) sin(2 * pi * x) + cos(3 *pi * x);

%define interval
n = 33; %number of data points
d = 7; %degree of least squares polynomial
x_train = linspace(-1 , 1 , n);
y_train = f(x_train);

%use poly val for degree d polynomial approximation
%used poly val examples from
%https://www.mathworks.com/help/matlab/ref/polyval.html#d123e1107356
as
%reference

[p_part1, ~] = polyfit(x_train, y_train, d); %Used polyfit to fit a
seventh degree polynomial to the data.

                                % p: function
values,

                                % S: standard
error for prediction

p_eval_part1 = polyval(p_part1 , x_train); %evaluates model at
all training points for plotting

%plotting provided in plotting section of code
```

Part 2 (Create testing data):

```
%generatee 100 random points between on the interval [-1,...,1]

%using matlab documentation on rng and rand, in addition to the
homework 9
%.m files as reference

rng('shuffle','twister');
x_test = -1 + (1 + 1)*rand(100,1);
x_test = sort(x_test); %order array for plotting

y_test = f(x_test);

% for degree = 1 -> 31 compute least squares coefficients of
polynomial of
% degree d with training data as last problem. imported functions
below

%obtain size of x data for vandermonde
size_train = size(x_train);
%initialize arrays
err_poly = zeros(31,1);
err_chol = err_poly;
err_QR = err_poly;
cond_ata = err_poly;
con_vander = err_poly;
for d = 1:31
    [p_part2, ~] = polyfit(x_train, y_train, d); %Used polyfit to fit
a seventh degree polynomial to the data.
                                                    % p: function
values,
                                                    % S: standard
error for prediction

    p_eval_part2 = polyval(p_part2 , x_test); %evaluates model at
all training points for plotting

    %obtain vandermonde matrix
    %initialize
    A_vander = zeros(size_train(2) , d+1);
%i think this is inefficient but im tired lol
    for i = 1 : size_train(2)
        A_vander(i,:) = x_train(i);
    end
    %raise elements to power (d+1 columns)
    for i = 0 : d
        A_vander( : , i + 1) = A_vander(: , i + 1).^i;
    end

    %now find coefficients using fucntions from hw 8
```

```

        [c_chol, cond_ata(d)] =
method_NormEq_Cholesky(A_vander,y_train'); %adjust to vertical for
function
        c_QR = method_ThinQR(A_vander, y_train', 0); %adjust to vertical
for function

        %only evaluate cholesky if matrix was sym pos def matrix is not
nan
        if (sum(isnan(c_chol(:))) < 1)
                %flip for poly val function
                c_chol = flip(c_chol);

                %evalutate polynomials for c_chol and c_QR
                p_chol = polyval(c_chol, x_test);

                %compute error
                err_chol(d) = norm(y_test - p_chol) / norm(y_test);

        else
                %if error doesnt make sense
                %for plotting and discussion sake change value to 10^0;
                err_chol(d) = 1;

        end
        %obtain condition number for vandermonde
        con_vander(d) = cond(A_vander);
        %flip for poly val function
        c_QR = flip(c_QR);

        %evaluate polynomial for c_qr
        p_QR = polyval(c_QR, x_test);

        %compute error
        err_poly(d) = norm(y_test - p_eval_part2) / norm(y_test);
        err_QR(d) = norm(y_test - p_QR) / norm(y_test);
end

%error plotting in plot section

```

Extra credit

```

x_extra = [1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 17];
y_extra = [89 105 125 159 227 331 444 564 728 1000 1267 1645 2204 2826
3485 7038];
y_extra_log = log10(y_extra);

%for non log

%need more testing points ig
rng('shuffle','twister');
x_test_extra = 1 + (17 - 1)*rand(30,1);
x_test_extra = sort(x_test_extra); %order array for plotting

```

```

%obtain vandermonde matrix, no need to flip
vand_extra = vander(x_extra);

%get least squares coefficients, flip y for dimensions
c_extra = vand_extra\y_extra';

%evaluate
p_extra = polyval(c_extra, x_test_extra);
ex = find(p_extra<0);
p_extra(p_extra < 0) = [];
x_test_extra(ex) = [];
%for log
c_extra = vand_extra\y_extra_log';
p_extra_log = polyval(c_extra, x_test_extra);

growthrate = (p_extra(14) - p_extra(11)) / p_extra(11) ;
doubletime = (x_test_extra(14)-x_test_extra(11)) * (log(2) /
    log(1+growthrate));

Warning: Matrix is close to singular or badly scaled. Results may be
inaccurate. RCOND = 1.548594e-24.
Warning: Matrix is close to singular or badly scaled. Results may be
inaccurate. RCOND = 1.548594e-24.

```

Interpretation

```

fprintf('\n-----\n')
fprintf('Analysis:')
fprintf('\n-----\n\n')
fprintf(['Initailly looking at the graph, when d = 19 the error for
the method using normal equations with cholesky factorization is not
included and set to 1. \n' , ...
'this is due to the following operation A_vander'*A resulting in
an ill-conidtioned, non-symettric positive definite matrix which
introduces round-off error causing cholesky to fail.\n ' , ...
'therefore it does not make sense to include this error. The condition
number for the vandermonde matrix was recorded for d = 1, ... , 31
and as expected around d = 20, cholesky failed. \n ' , ...
'what was not expected was it seems the error of both methods QR
and NE decreased as the condition number of the vandermonde system
increased. \n',...
'I dont really understand why this is but might be due to the
fact the degree of the polynomial remains well below the number of
training data points being used\n\n'])

fprintf(['After adjusting the number of training data points to be
less than the maximum degree d used to compute the least-squares
coefficients ( n <= d ) , the error significantly increased whenever
a polynomial of degree d was fit to a smaller amount of training
data.\n ' , ...

```

```

'i re-ran the code with 10 evenly spaced points on the interval [-1,1]
for the training data. \nas the polynomial degree increased past 10
the normalized testing error increased as the condition number of the
vandermonde system increased. \n ',...
'so to sum up this long probably wrong analysis, my interpretation is
the condition number of the matrix in the least-squares problem plays
a minor role in the overall accuracy of each method. \n',...
'As long as the degree of polynomial remains less than or equal to the
number of training points, the accuracy of the QR and Normal equation
method will increase as the polynomial degree increases.']]);
fprintf('\n\nsorry about this long analysis')

fprintf('\n-----
\n')
fprintf('Extra Credit:')
fprintf('\n-----
\n\n')
fprintf('My log linear model does seems to model the growth accurately
except for the initial first three and last three data points,
doubling time from least squares fit around %0.4f days. \ni got tired
and the extra credit is sketchy',doubletime)

```

Analysis:

Initailly looking at the graph, when $d = 19$ the error for the method using normal equations with cholesky factorization is not included and set to 1.

*this is due to the following operation $A_vander'*A$ resulting in an ill-conidtioned, non-symettric positive definite matrix which introduces round-off error causing cholesky to fail. therefore it does not make sense to include this error. The condition number for the vandermonde matrix was recorded for $d = 1, \dots, 31$ and as expected around $d = 20$, cholesky failed. what was not expected was it seems the error of both methods QR and NE decreased as the condition number of the vandermonde system increased.*

I dont really understand why this is but might be due to the fact the degree of the polynomial remains well below the number of training data points being used

After adjusting the number of training data points to be less than the maximum degree d used to compute the least-squares coefficients ($n \ll d$), the error significantly increased whenever a polynomial of degree d was fit to a smaller amount of training data.

i re-ran the code with 10 evenly spaced points on the interval [-1,1] for the training data.

as the polynomial degree increased past 10 the normalized testing error increased as the condition number of the vandermonde system increased.

so to sum up this long probably wrong analysis, my interpretation is the condition number of the matrix in the least-squares problem plays a minor role in the overall accuracy of each method. As long as the degree of polynomial remains less than or equal to the number of training points, the accuracy of the QR and Normal equation method will increase as the polynomial degree increases.

sorry about this long analysis

Extra Credit:

*My log linear model does seems to model the growth accuratly except for the initial first three and last three data points, doubling time from least squares fit around 2.6238 days.
i got tired and the extra credit is sketchy*

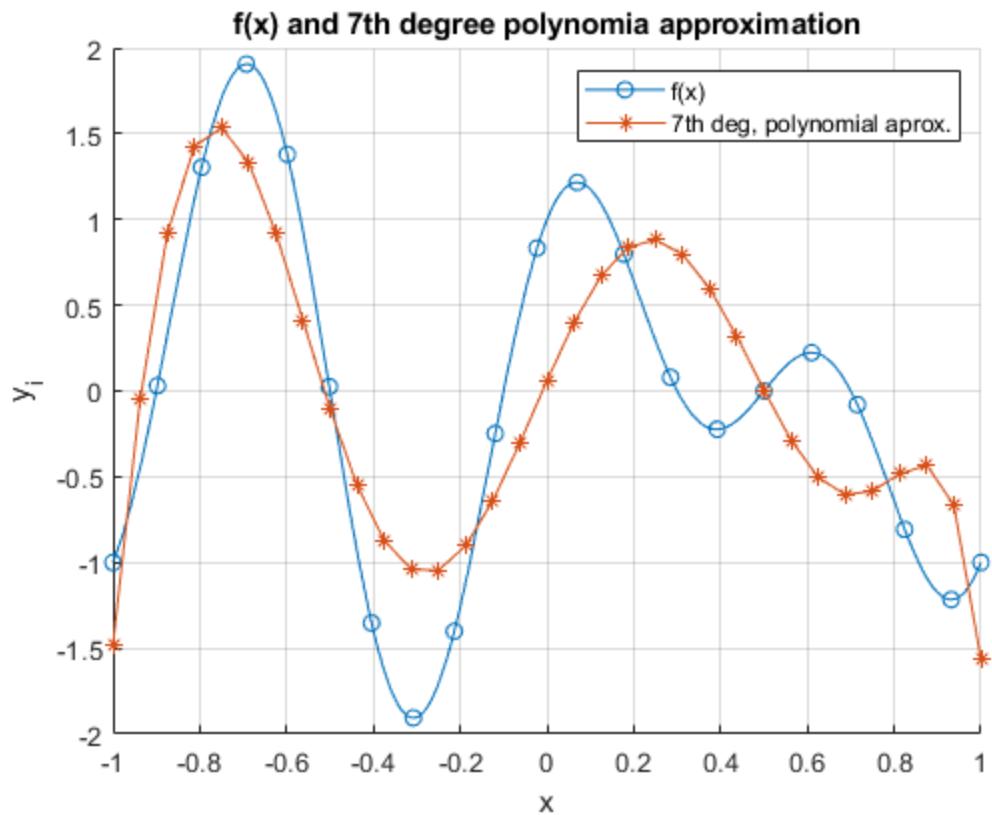
Plotting

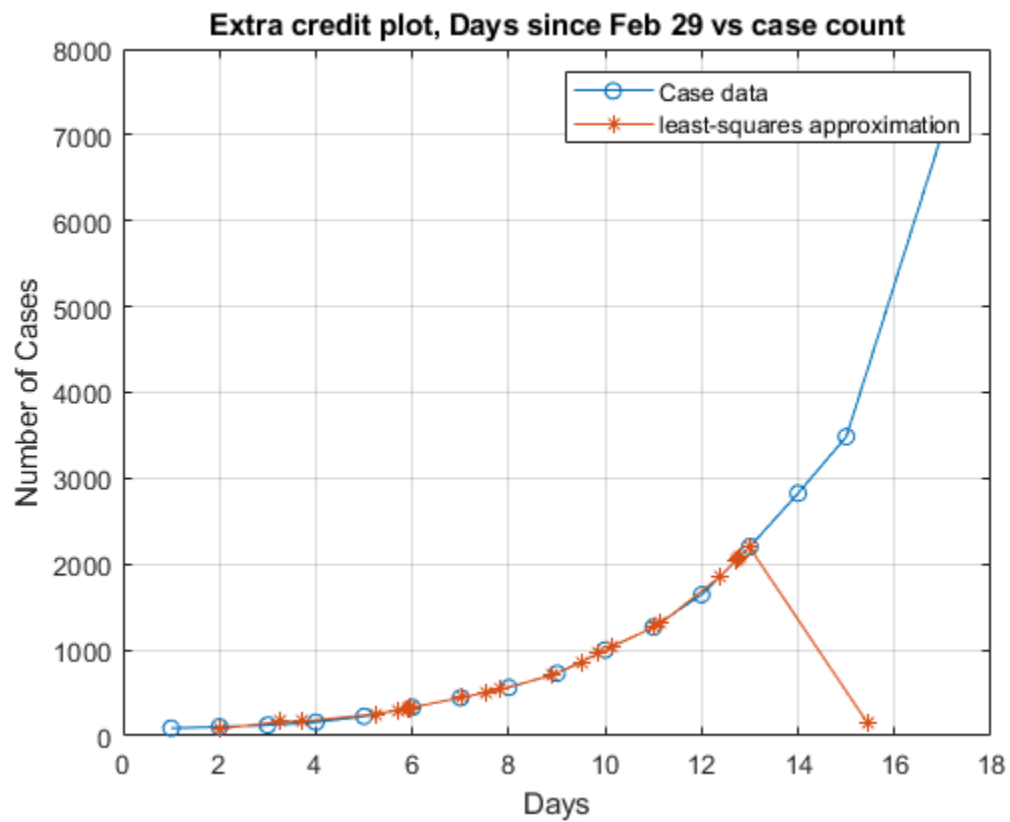
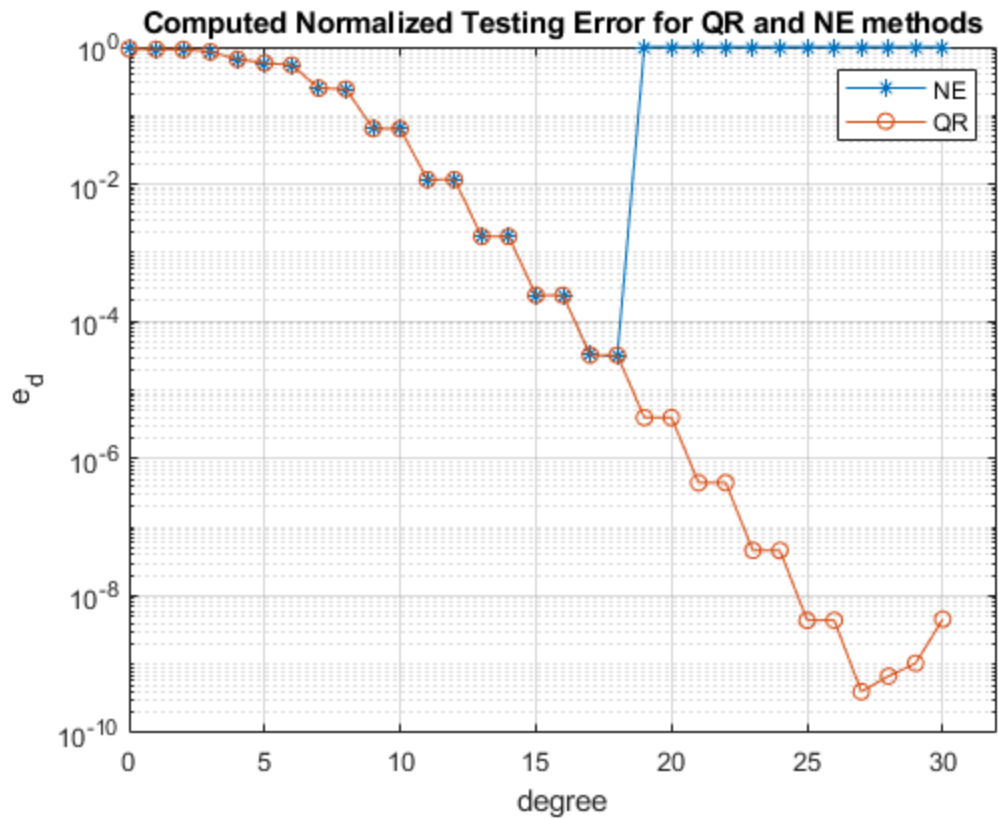
```
% seventh degree polynomial approximation
figure(1)
hold on;
fplot(f,[x_train(1) , x_train(end)], '-o') %plot function
plot(x_train, p_eval_part1, '-*');
grid on;
title('f(x) and 7th degree polynomia approximation')
xlabel('x')
ylabel('y_i')
legend('f(x)' , '7th deg, polynomial aprox.')
hold off;
snapnow
%error for QR vs NE
figure(2)
semilogy(0:30, err_chol, '-*' , 0:30, err_QR, '-o')
hold on;
grid on;
ylabel('e_d')
xlabel('degree')
xlim([0 32])
title('Computed Normalized Testing Error for QR and NE methods')
legend('NE','QR')
hold off;
snapnow
%extra credit plot
%non log
figure(3)
plot(x_extra, y_extra, '-o')
hold on;
plot(x_test_extra, p_extra, '-*')
grid on;
title('Extra credit plot, Days since Feb 29 vs case count')
legend('Case data', 'least-squares approximation')
xlabel('Days')
```

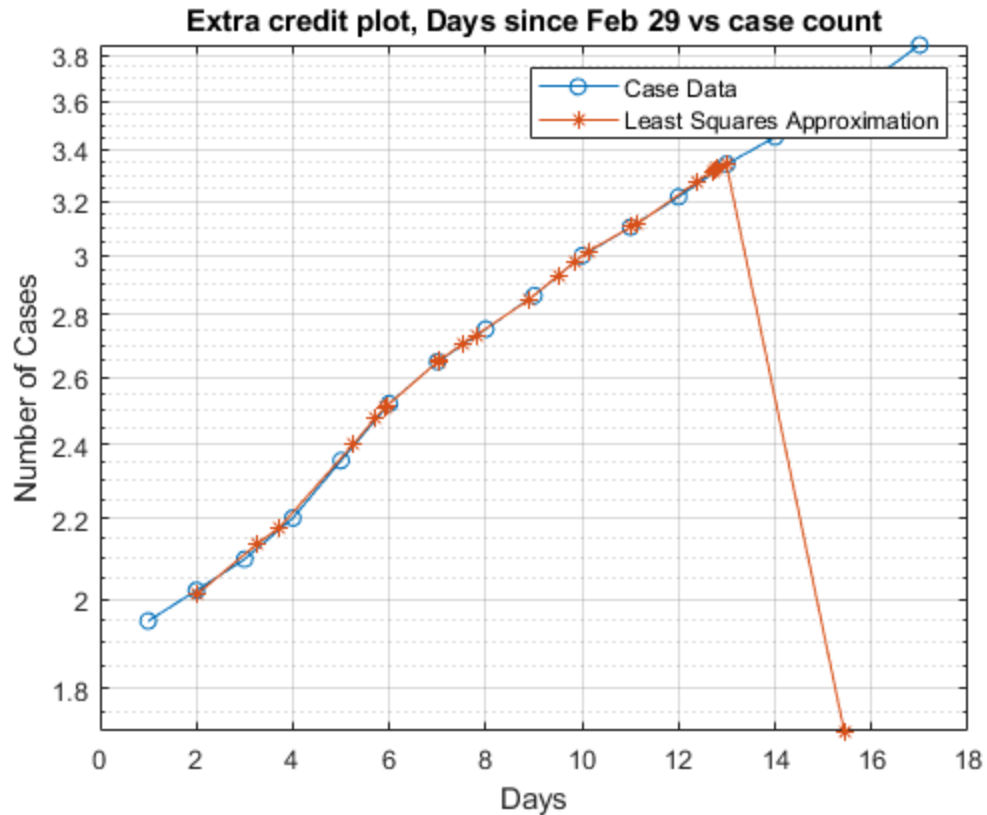
```

ylabel('Number of Cases')
hold off;
    snapnow
%log
figure(4)
semilogy(x_extra, y_extra_log, '-o', x_test_extra, p_extra_log, '-*')
hold on;
grid on;
xlabel('Days')
ylabel('Number of Cases')
title('Extra credit plot, Days since Feb 29 vs case count')
legend('Case Data', 'Least Squares Approximation')
hold off;
    snapnow
%figure

```







Functions

```
function [x, con_vand] = method_NormEq_Cholesky(A,b)
%{
    Prupose: Matlab implementation of method to solve least squares
    problem using normal
    equations with cholesky
    Inputs:
        A: LHS matrix for Ax = b
        b: RHS matrix for Ax = b
    output:
        x: variable matrix x in Ax = b (x) which minimizes
        ||b-Ax||_2^2
%}

%form A^T*A e R^n*n and A^T*b e R^n
ata = A'*A;
atb = A'*b;

%Solve normal eqns, (A^T*A)x = A^T*b for x
%first lets double check
%get size to make sure A = n x n
size_A = size(ata);
%check rank
r_ata = rank(ata);
```

```

%updated for hw9
con_vand = cond(ata);
if( (size_A(1) == size_A(2) ) && ( r_ata == size_A(1) ) )
    %matrix is sym, pos def, compute and solve cholesky
    factorization (
        %determine variable vector using cholesky factorization
        R = chol(ata);
        x = R\' \atb);

else
    %cant use error func for this homework so itll break, if using
    %outside of hw uncomment
    %error('Matrix is not Symmetric Positive Definite')
    %warning does not apply to this hw so it will be adjusted
    %if this error occurs create nan array maybe later could be
    used as a flag in
    %error calc
    siz_atb = size(atb);
    warning('Error not accounted for due to d_%i vandermonde not
    sym pos def', siz_atb(1))
    x = NaN(siz_atb);
end

end

function [ x ] = method_ThinQR(A, b, bool)
%{
    Purpose: Matlab implementation to solve the linear least-squares
    problem using a method based on Thin QR factorization
    Input:
        A: LHS matrix, Ax = b
        b: RHS matrix, Ax = b
        bool: boolean value, 1 if you want to use my janky code which
    seems
        wrong, or built in qr function that works
    Output:
        x: variable matrix x in Ax = b (x) which minimizes
        ||b-Ax||_2^2
%}

%alright so because i am trying to do both the homeowkrs this weekend
im
%assuming the grant-schmidt orthogonalization and least squares is
similar
%to that of the thin QR decomp in lecture. Sauer's numerical analysis
and
%https://ocw.mit.edu/courses/mathematics/18-06-linear-algebra-
spring-2010/related-resources/MIT18_06S10_gramschmidtmat.pdf
%were used as a reference

```

```
%compute the thin QR decomposition
```

```
if bool
    %obtain size of A
    size_A = size(A);

    %initialize r matrix. upper right traingular n x n
    r = zeros(size_A(2),size_A(2));
    %initialize q tall matrixx orthonormal columns, m x n
    q = zeros( size_A );

    %Grant-Schmidt orthogonalization
    for j = 1 : size_A(2)

        y = A(:,j);

        for i = 1 : j-1

            r(i,j) = q(:, i) ' * A(:, j);
            y = y - r(i,j) * q(:, i);

        end
        r(j , j )= norm(y);
        q(:,j) = y/r(j , j);

    end
else

    % if this doesnt work just use qr matlab
    [q,r] = qr(A, 0);
end
% After thin QR is computed, finish computation
b_til = q'*b;

% Solve
x = r\b_til;

end
```

```
Warning: Error not accounted for due to d_21 vandermonde not sym pos
def
Warning: Error not accounted for due to d_22 vandermonde not sym pos
def
Warning: Error not accounted for due to d_23 vandermonde not sym pos
def
Warning: Error not accounted for due to d_24 vandermonde not sym pos
def
Warning: Error not accounted for due to d_25 vandermonde not sym pos
def
Warning: Error not accounted for due to d_26 vandermonde not sym pos
def
Warning: Error not accounted for due to d_27 vandermonde not sym pos
def
```

Warning: Error not accounted for due to d_28 vandermonde not sym pos
def
Warning: Error not accounted for due to d_29 vandermonde not sym pos
def
Warning: Error not accounted for due to d_30 vandermonde not sym pos
def
Warning: Error not accounted for due to d_31 vandermonde not sym pos
def
Warning: Error not accounted for due to d_32 vandermonde not sym pos
def

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