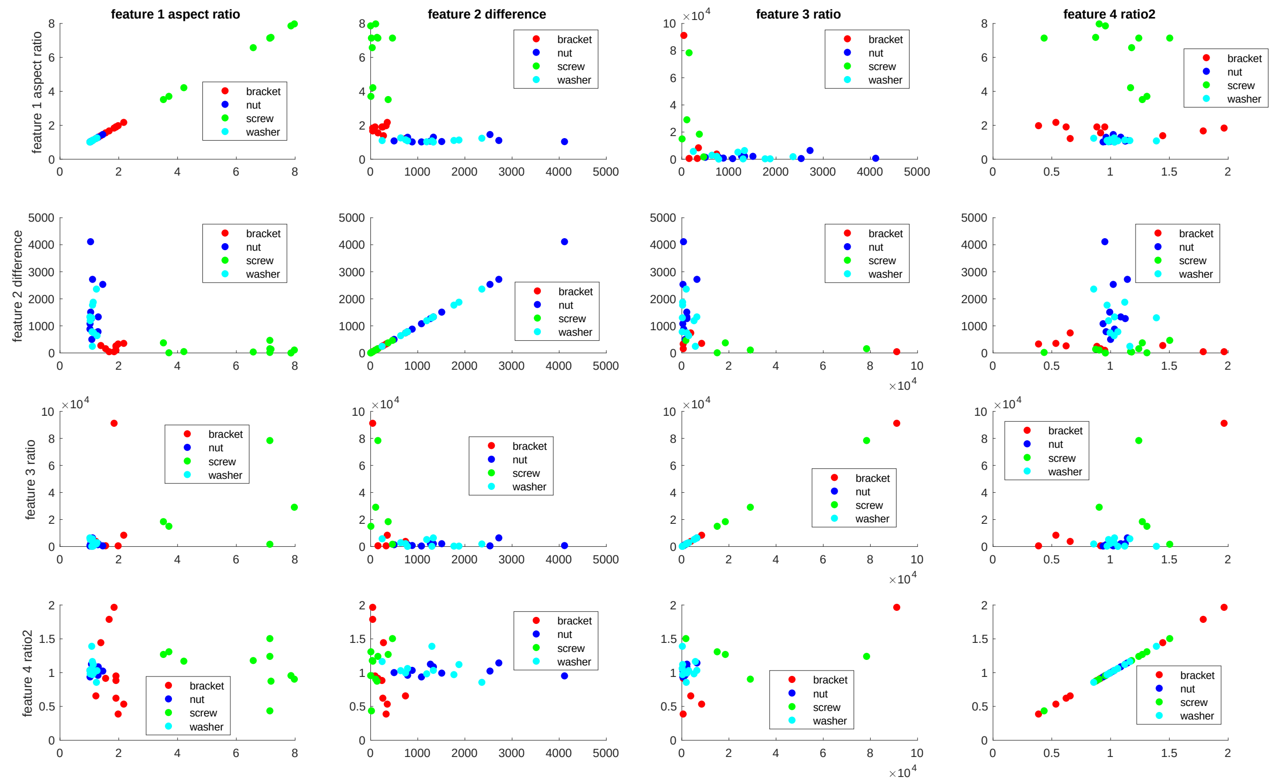
Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

1-)

a-)

- Feature 1 is the aspect ratio feature "AR", in this code it uses the region props function in Matlab to extract the lengths from each image. The idea is that this should separate the screws from everything else because they have the largest ration of major to minor axes. This indeed provides very good separability with the screws after running the code in the appendix.
- Feature 2, labeled "difference" takes the difference between the binarized image after closing all of the holes. The idea is that after the holes are closed in the image, the amount of 1's in the binary will increase because this space is now white. White corresponds to 1, and black to 0. After doing this, I subtracted the image that has the hole filled with the original binarized image. The difference for the washers and nuts should be much higher because the hole in the images for washers and nuts takes a large ratio of the image itself. Although brackets have holes, the holes themselves are typically a small ratio of the bracket, so the difference does not affect it as much as the washers and nuts. Finally, the screws have no holes, and should be affected the least by this algorithm, that is, have the smallest difference! Of course, all of the images are put into the same width and height to account for a larger image having more pixels. This code is seen in the appendix
- Feature 3, labeled "ratio" resizes each binary image and crops it in the center. The point of this, is that if it is a washer or a nut, the center will be a white space, and the ratio of black pixels to white pixels will be lower in this cropped image for washers and nuts as compared to brackets and screws.
- Feature 4, labeled "ratio2", was an attempt to separate washers and nuts. The idea was that due to a washer being more circular, it exhibits symmetry on all axes, as opposed to a nut which tends to have sides. Thus, if we split the image in have and take the difference between the left half and right half (in binary), we should have been able to see a bigger difference for the nuts due to a lack of symmetry, and difference closer to zero for the washers. The screws and brackets should have an even higher difference. However, this did not prove sufficient as seen in the subplots in part b below

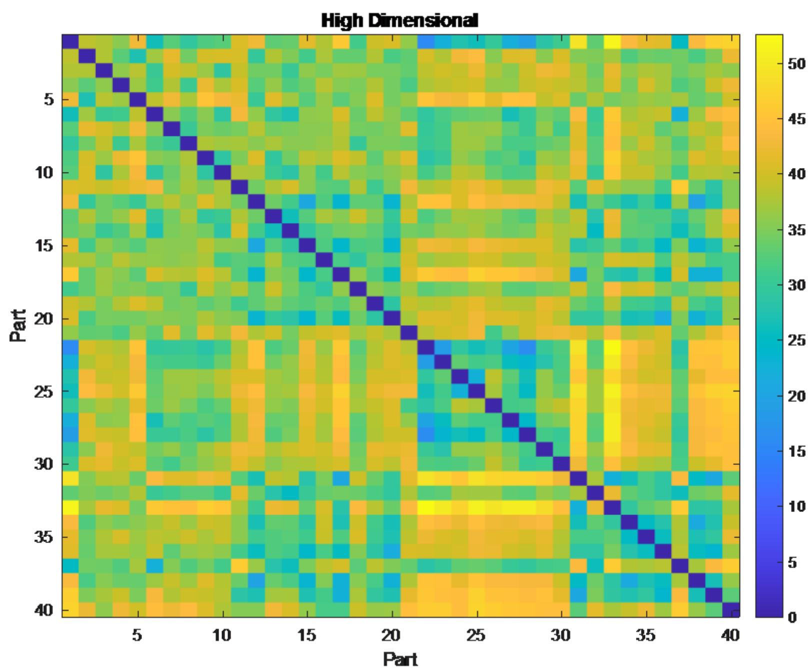
Assignment 1
Mahmood Mustafa Shilleh
02/05/2020
b-)

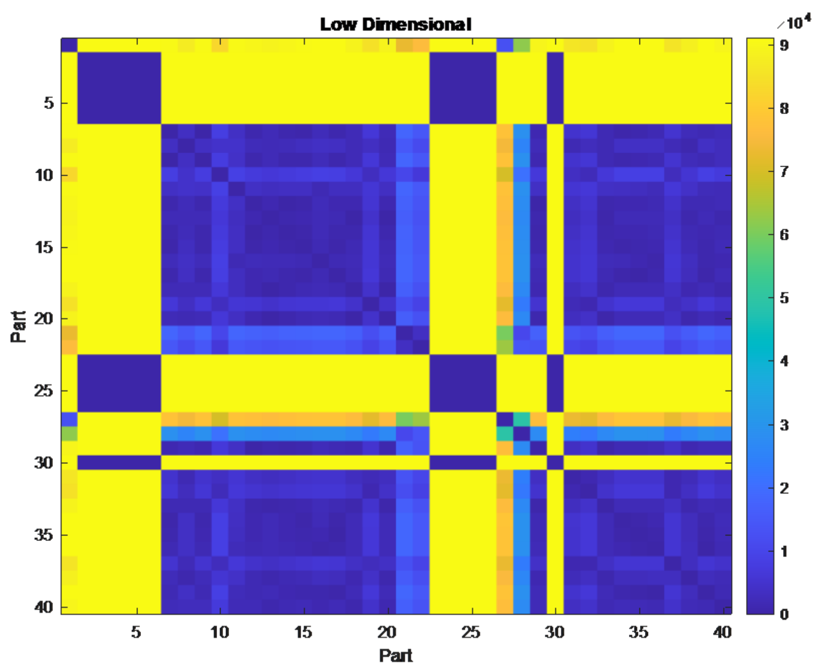



There is a total of 16 scatter plots, the column number corresponds to what feature is on the x-axis, same with the rows. Example, column 2 and row 3 is a scatter plot of f2 vs f3. According to the above figure we can see the clusters separated in some of the plots. F1 vs all the other features show a great amount of separability because the screws are in their own cluster. The "difference" feature also provided a great deal of separability as can been seen in F2 vs all other features, the blue and the cyan color corresponding to washers and nuts for their own cluster, which is great because it means the feature works. The "difference" combined with the aspect ratio as shown in subplot f1 vs f2 gives us a nice cluster for the bracket. Feature 3 also does what its intended to do by create a cluster for washers and nuts specifically. Finally, it can be seen that feature 4 is not successful in separating washers and nuts.

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

c-)



Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

Note: Part (1-10) corresponds to bracket, (10-20) to nuts, (20-30) for screws, and (30-40) washers. In the figures above, the high dimensional example tells us little in terms of separability because it takes the difference in the pixels of each in binary. We can kind of see nuts and washers being similar from this since the space shared between them is less than 30 on the colormap. Pure blue means the image is similar and that makes sense because the pixels are being subtracted from themselves, so it should be zero along the diagonal as seen. On the other hand, the low dimensional image gives us a degree of separability other than the diagonal as can be seen in the blue regions. This means that the feature space is successful in those areas.

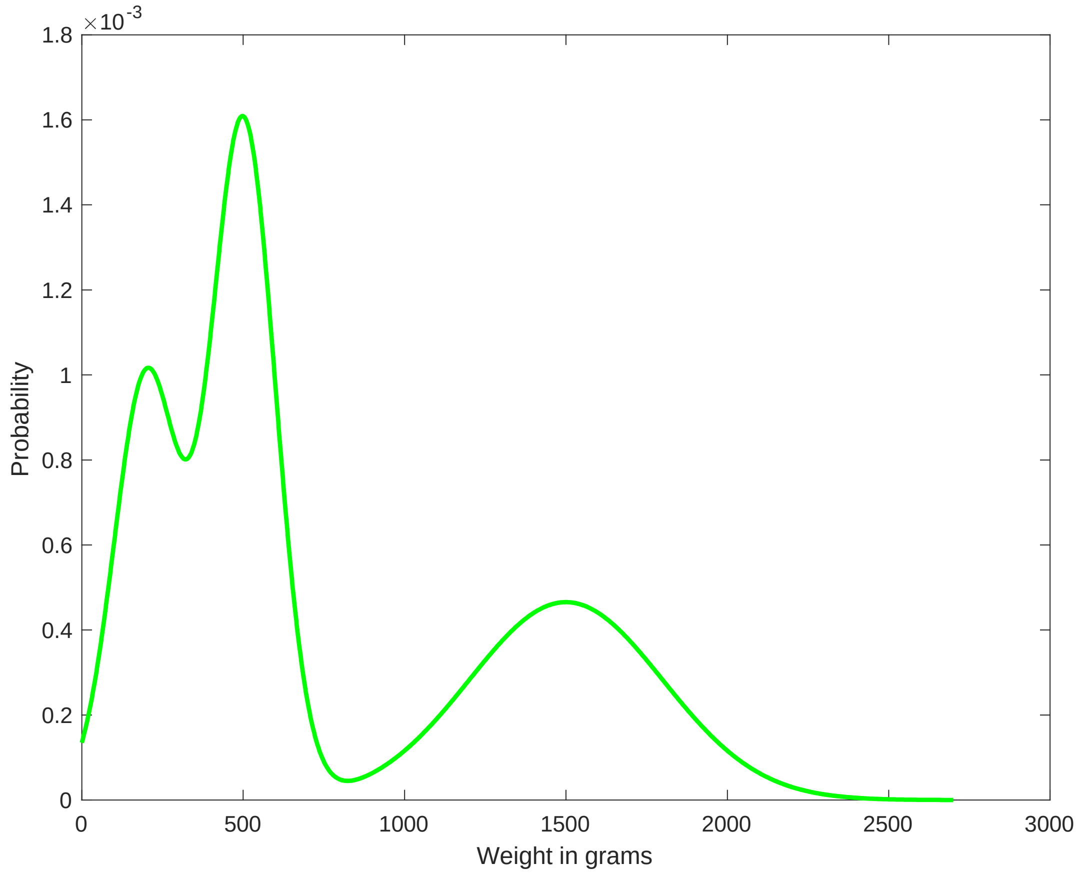
Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

2-)

a-)

Here is the combined pdf of the three distributions, combined as seen in the appendix:



Assignment 1
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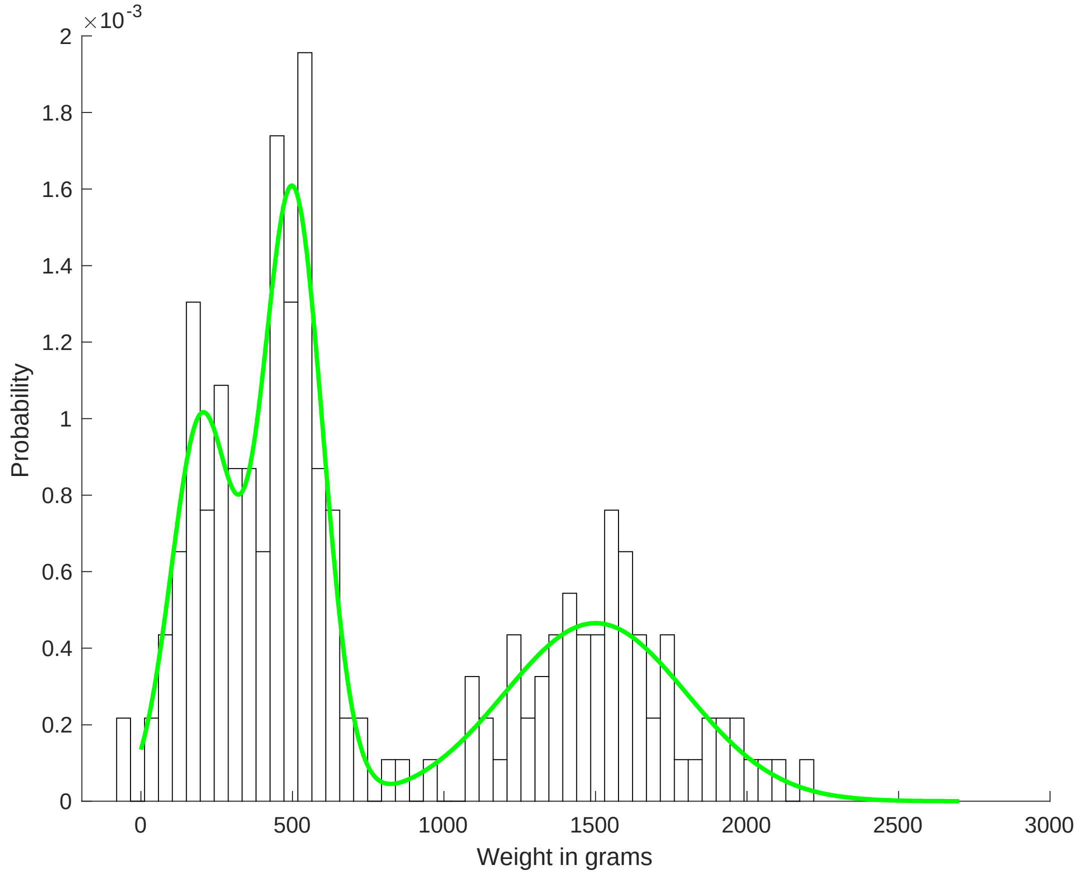
02/05/2020

b-)




c-)

Yes the theoretical and experimental results are rather close, however there needs to be more examples to get better results because there is a large variation in weight.

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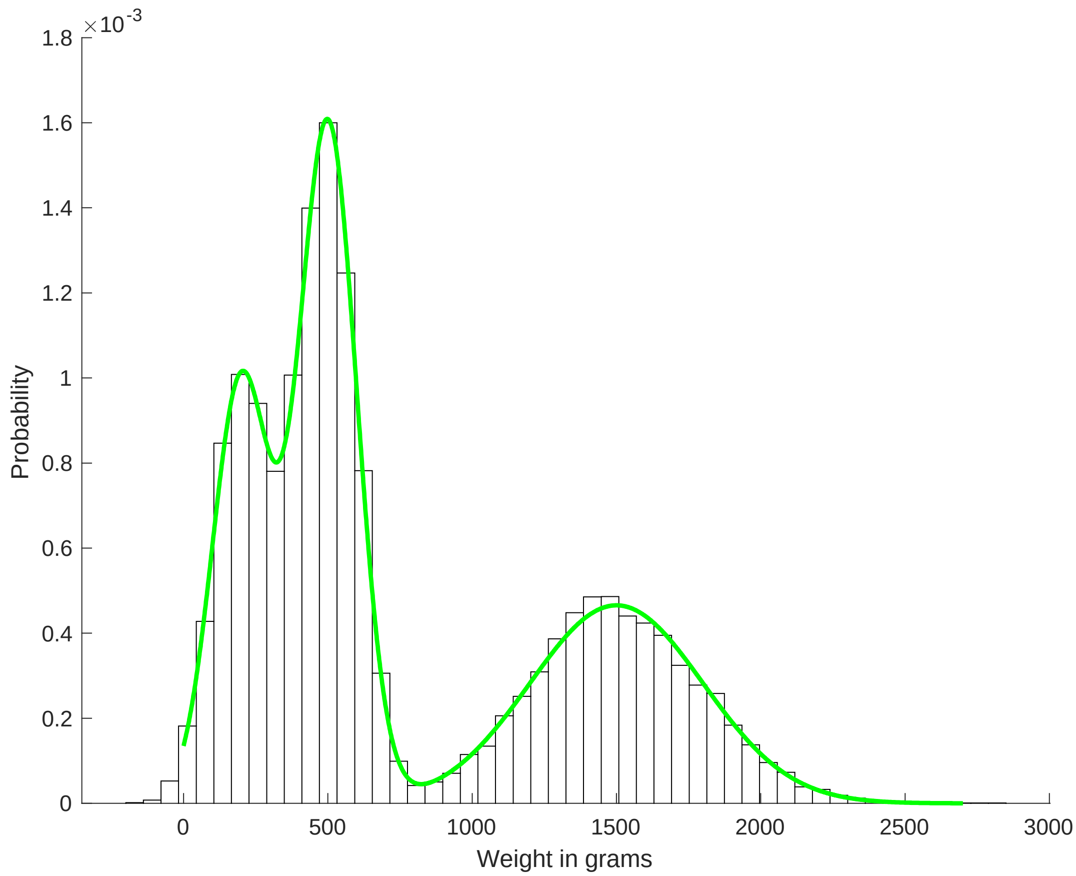
02/05/2020

d-)




The theoretical and experimental distributions match again, proving that the sampling method works.

e-)

The results show that as N increases the histogram behavior gets closer to matching the gaussian distribution, as expected in the theory. As N gets infinitely large and the bin sizes thin out it will eventually fill in the area beneath the curve perfectly

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

3-)

a-) The equations to solve these problems are taken from Lecture 4, and are as follows:

$$\Lambda_{ML}(x) = \frac{p(x|\omega_1)}{p(x|\omega_2)} \gtrless 1$$

$$\Lambda_{MAP}(x) = \frac{p(x|\omega_1)}{p(x|\omega_2)} \gtrless \frac{P(\omega_2)}{P(\omega_1)}$$

$$\Lambda_{BAYES}(x) = \frac{p(x|\omega_1)}{p(x|\omega_2)} \gtrless \frac{P(\omega_2)}{P(\omega_1)}\frac{(C_{12} - C_{22})}{(C_{21} - C_{11})}$$

The Maximum likelihood criteria after solving in MATLAB (see appendix) gives:

$$x = 0.718, 1.532$$

Which means we pick $\omega_1$ if x is greater than 1.53 or less than 0.718 and we pick $\omega_2$ if its in between.

b-) The same code is used to generate values for the MAP estimation.

$$x = 1.125 \pm 0.205i$$

c-) Finally, the Bayes risk uses the same code but takes into account the cost and gives us the values of

$$x = 0.910, 1.340$$

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02/05/2020

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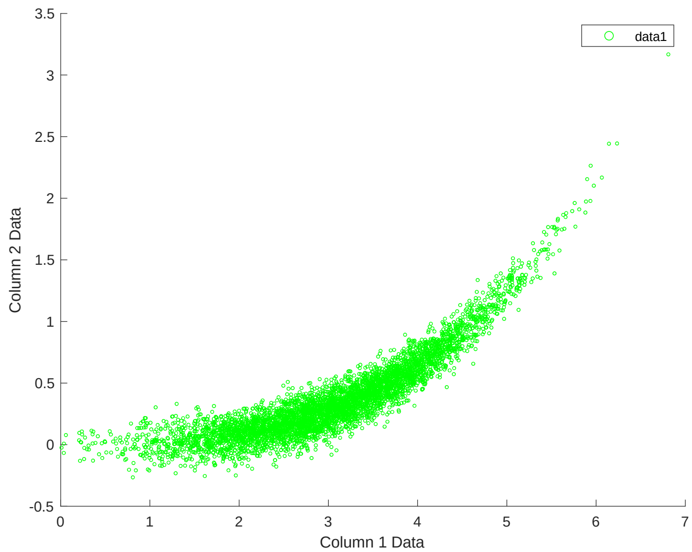
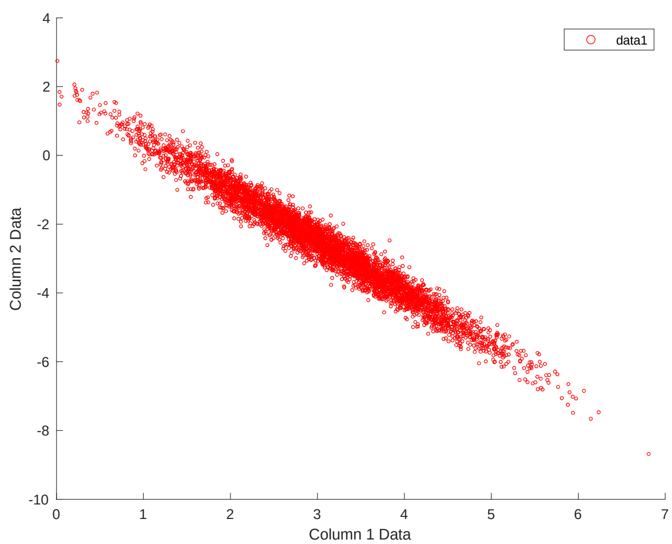
02/05/2020

4-)

**Part 1:**

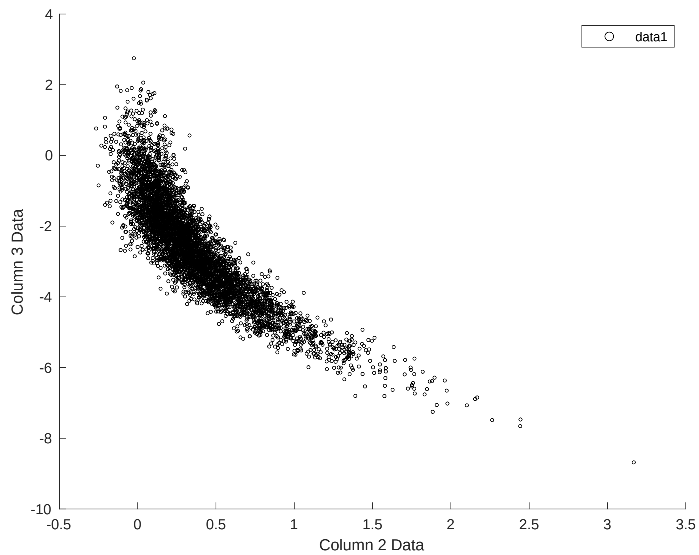



Correlation coefficient is definitely positive, somewhere between 0.5 and 1




Without doing any calculations it looks like the correlation coefficient is almost negative 1.

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020




Without doing any calculations the correlation coefficient looks to be between -0.5 and -1.

**Part 2:**

The covariance matrix, mean vector, and correlation coefficients are all generated using the code from the Appendix Section.

The covariance matrix for the first three figures in order are as follows and the correlation coefficients:

$\Sigma_1$:

| | |
|---|---|
| 0.97136798 | 0.29223774 |
| 0.29223774 | 0.1133424 |

$$\rho_{12} = 0.8807$$

$\Sigma_2$:

| | |
|---|---|
| 0.97136798 | -1.45366 |
| -1.45366 | 2.26436308 |

$$\rho_{13} = -0.9802$$

$\Sigma_3$:

| | |
|---|---|
| 0.1133424 | -0.4370509 |
| -0.4370509 | 2.26436308 |

$$\rho_{23} = -0.8627$$

Assignment 1
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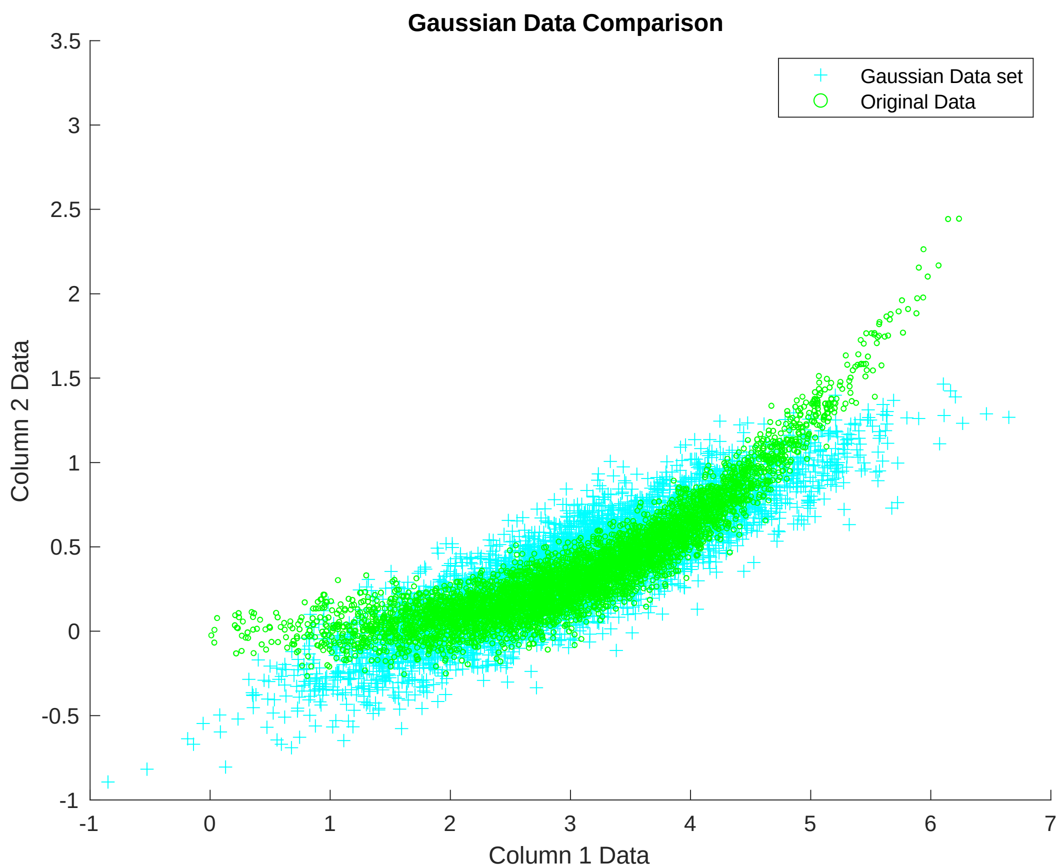
02/05/2020

μ:

3.03233925 0.36865054 -2.5518616

Yes, the off diagonal terms in the covariance matrix are very consistent with what we observe in the scatter plots due to the correlation coefficients that were calculated. The coefficients are very similar to the prediction and what we learned in class in terms of the shape!

**Part 3 and 4:**



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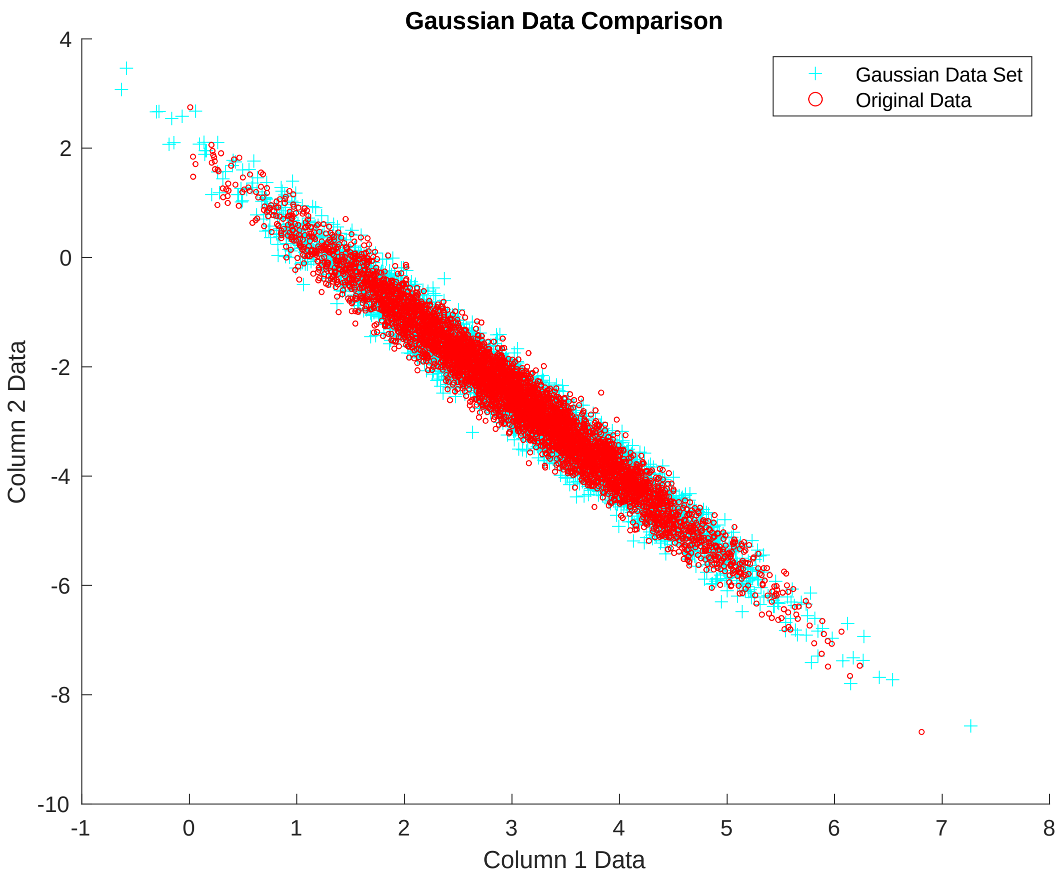

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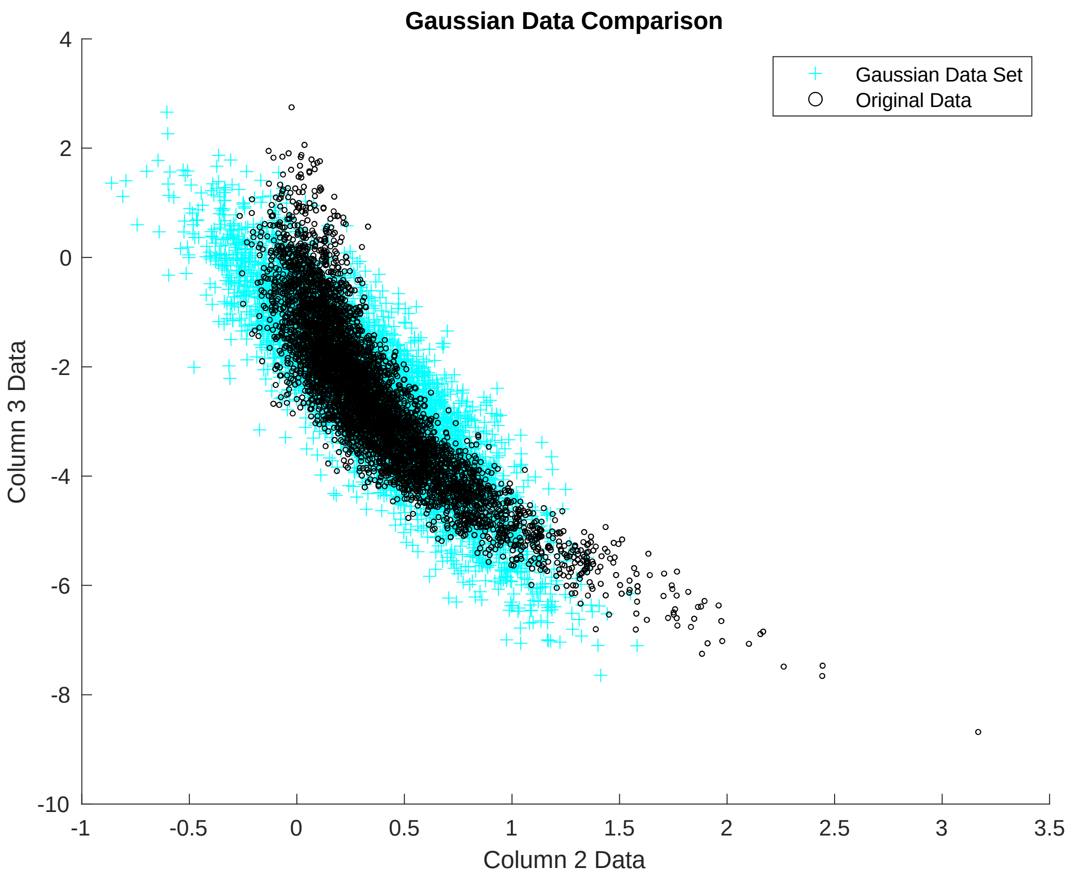


The scatter plots do not entirely match those generated in part 1. Although they are very similar! The issue is that the data itself does not behave entirely gaussian. It does not have the oval shape as discussed in class.

**Part 5:**

The results from the problem show that if we plot two datasets together we can tell based on the shape if they are correlated and how they are correlated. This proved to be true and consistent with the slope of the data set as seen in part 2! It is clear however that after estimating the data as a gaussian distribution with mean and covariance we can see there is a discrepancy, and this is to be expected considering the data itself is not perfectly elliptical.

Assignment 1
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02/05/2020

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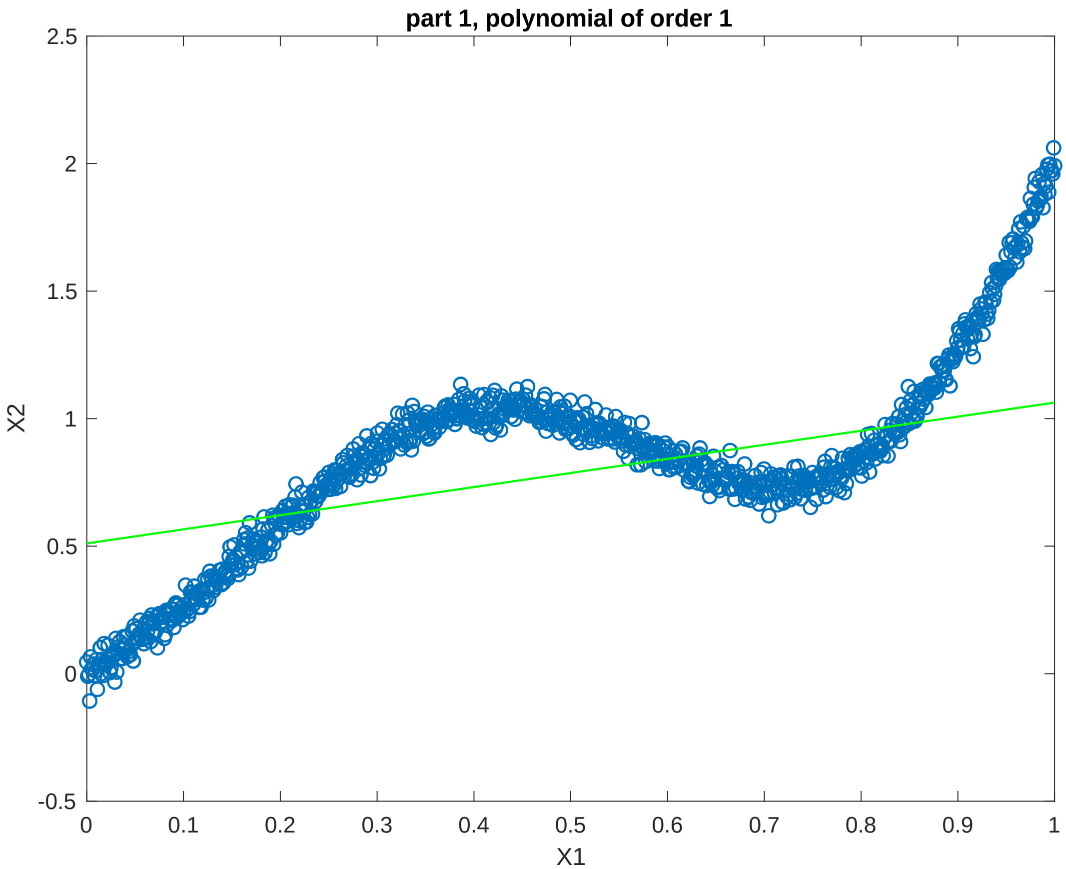
02/05/2020
5-)

**Part 1:**




The MSE for this polynomial is 0.0415

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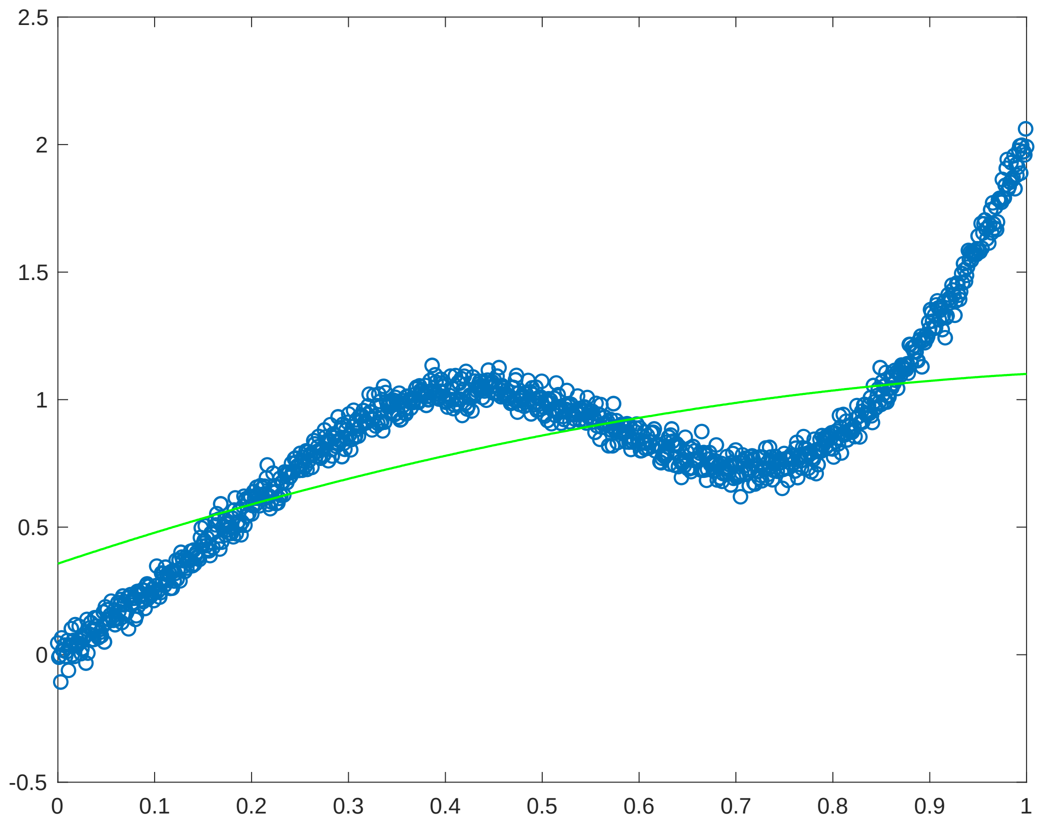
02/05/2020
**Part 2:**




Order 2

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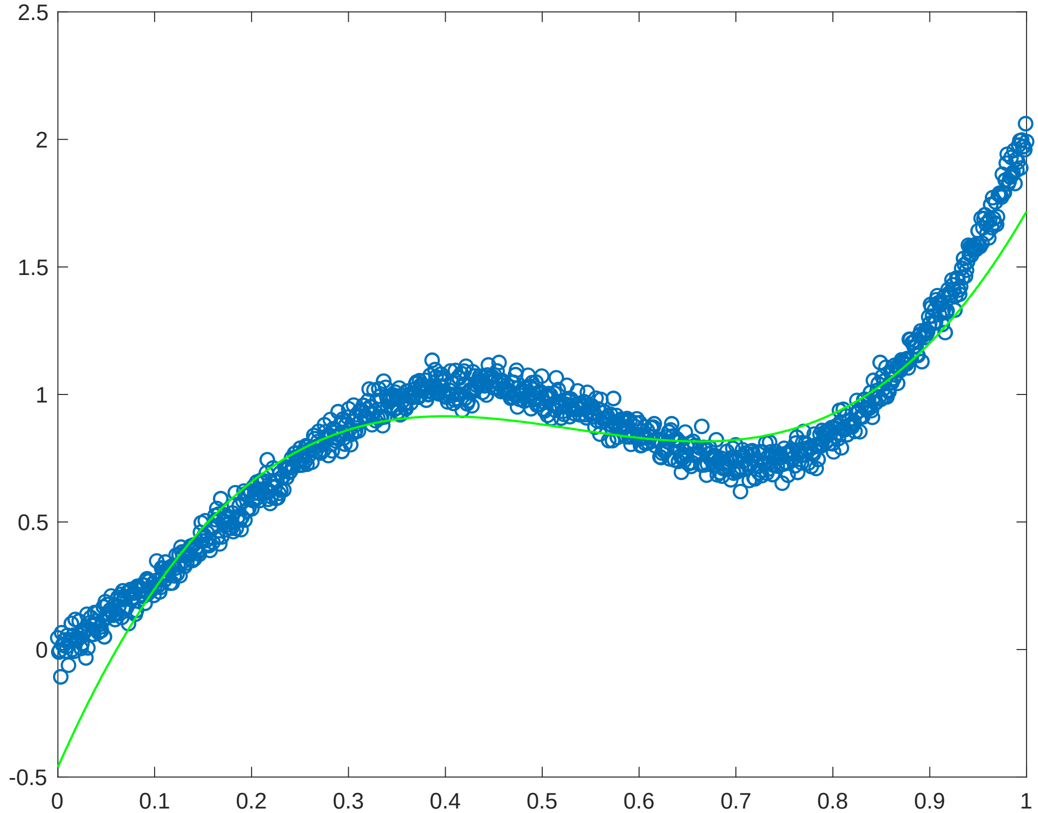


Order 3

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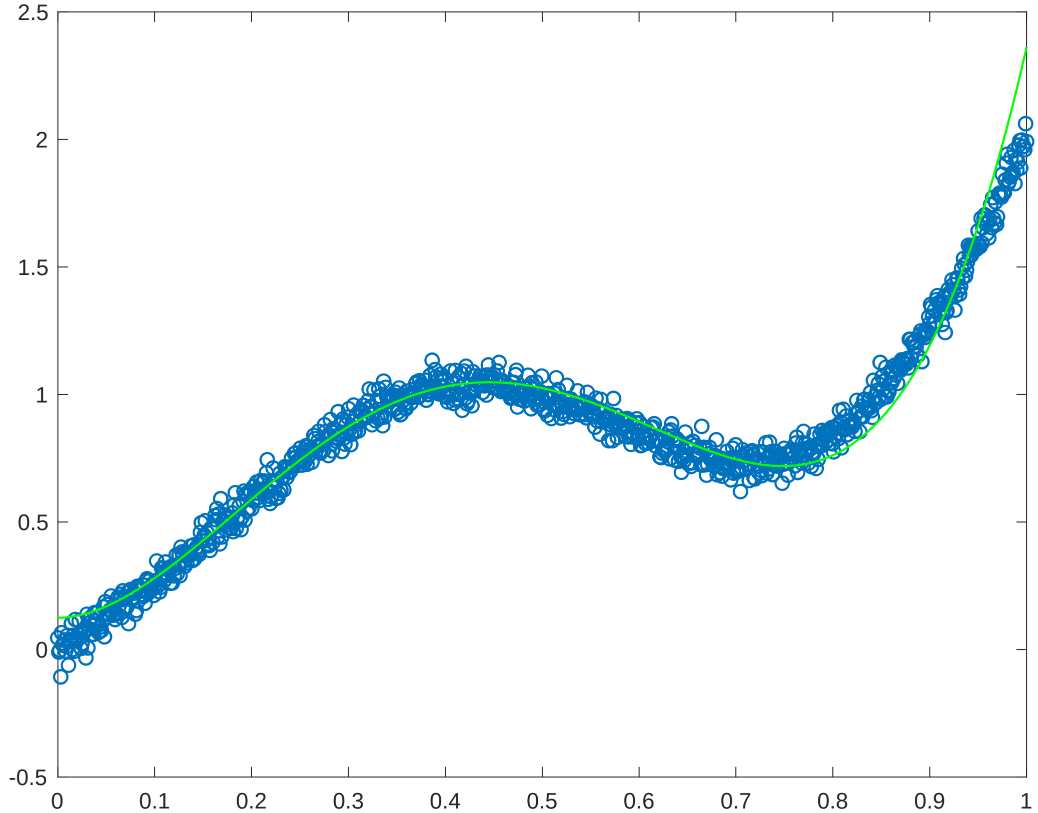


Order 4

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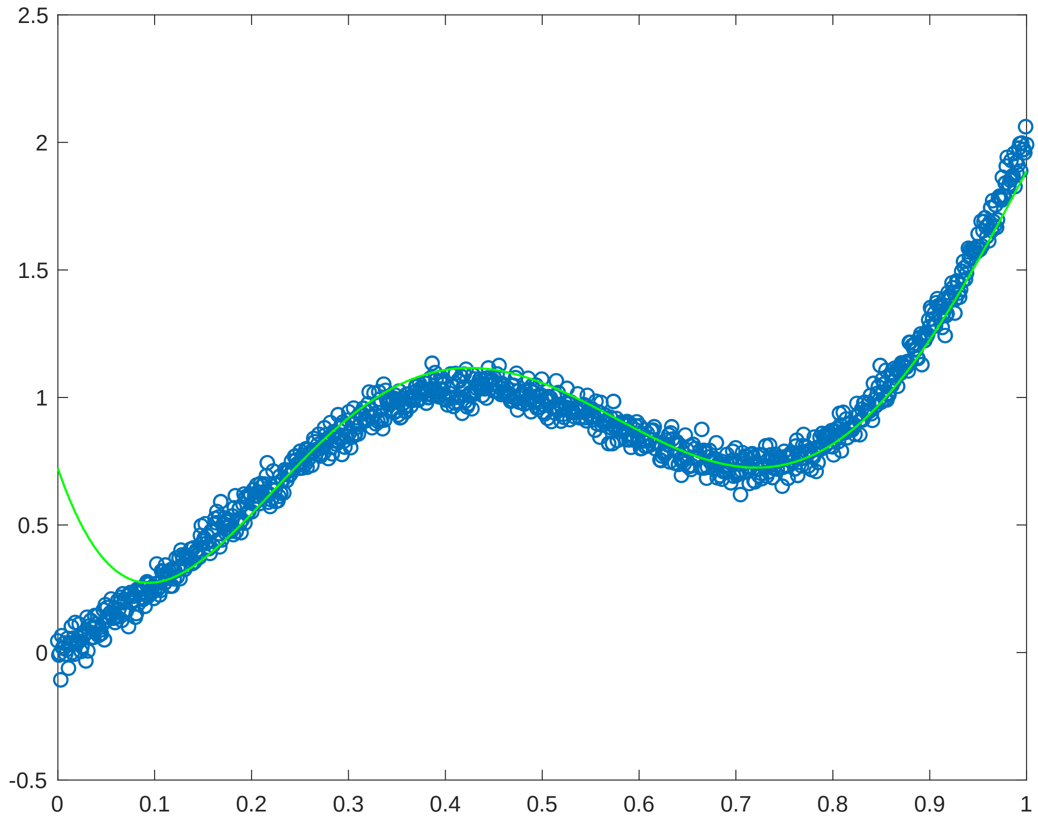


Order 5

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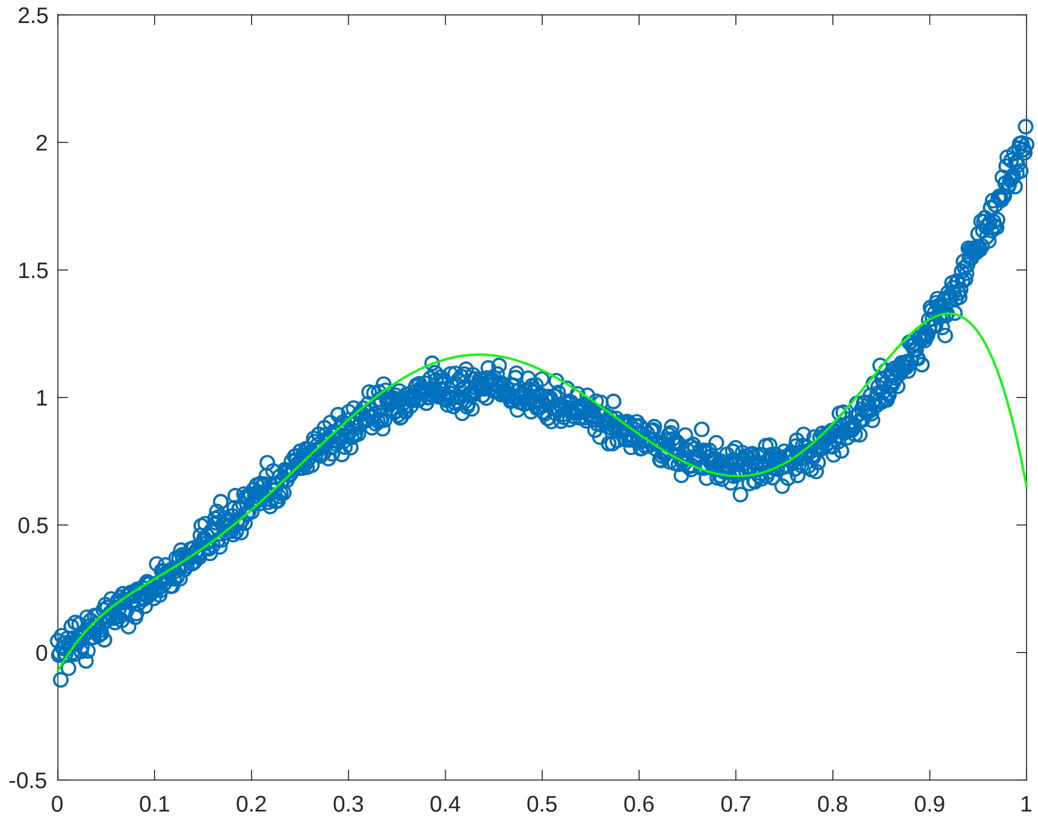


Order 6

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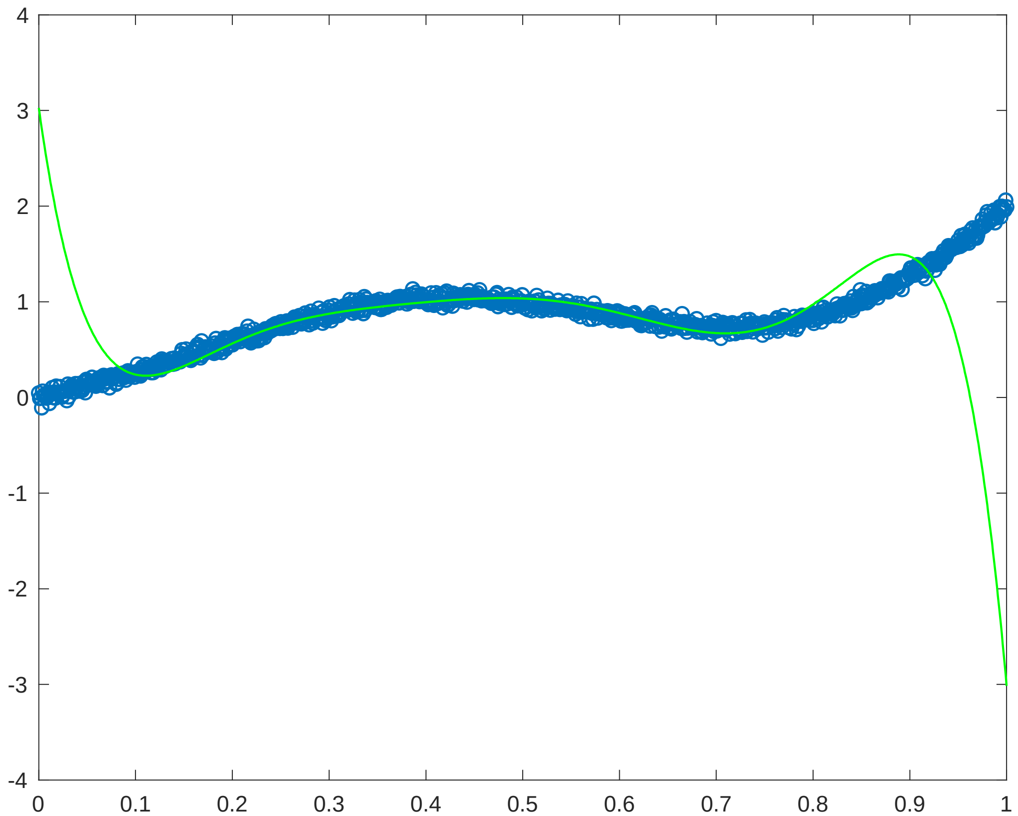


Order 7

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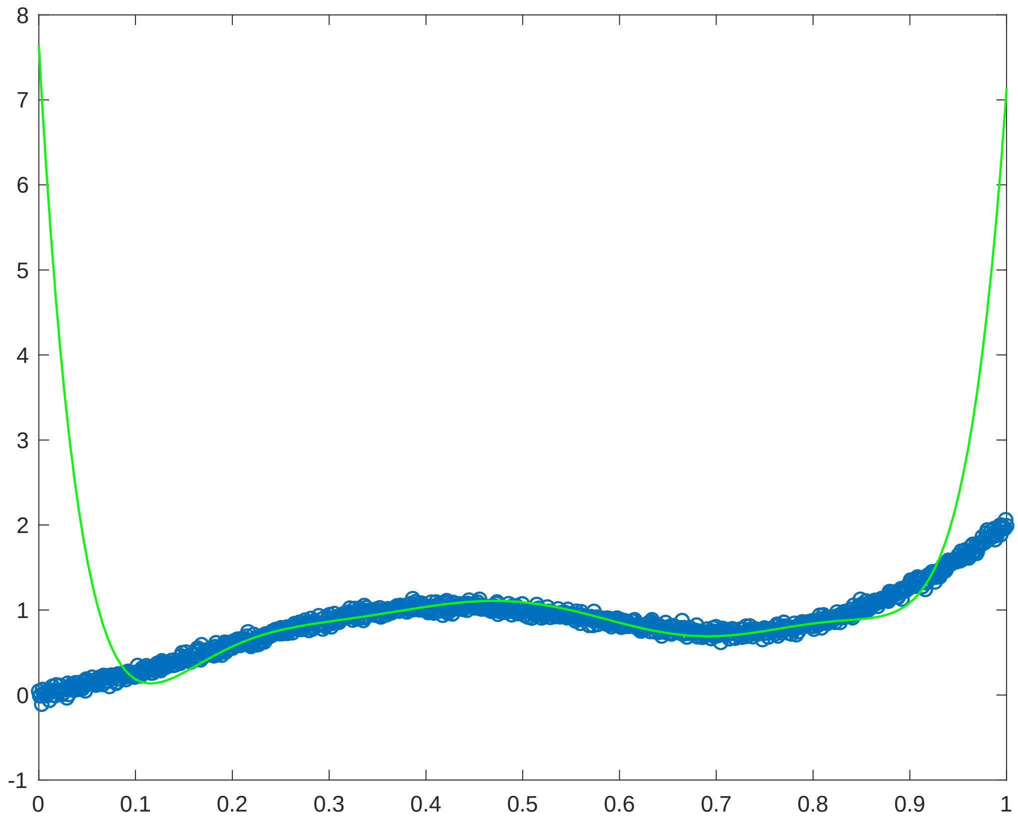


Order 8

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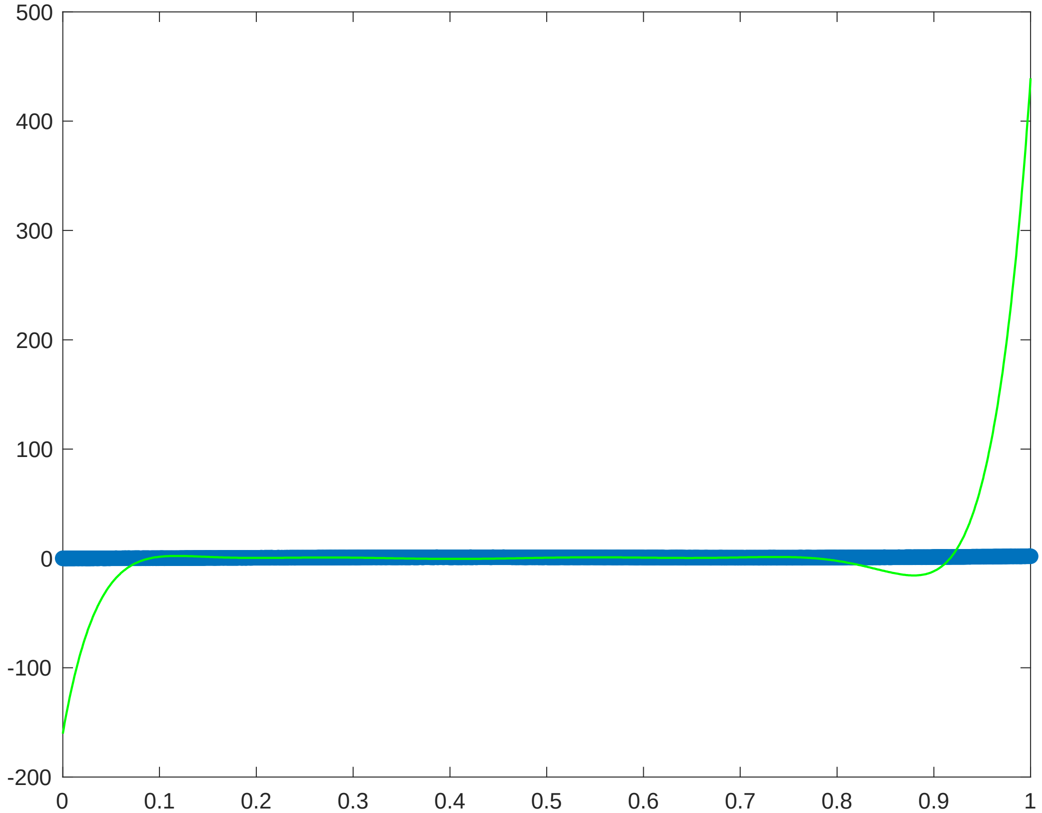


Order 9

Assignment 1
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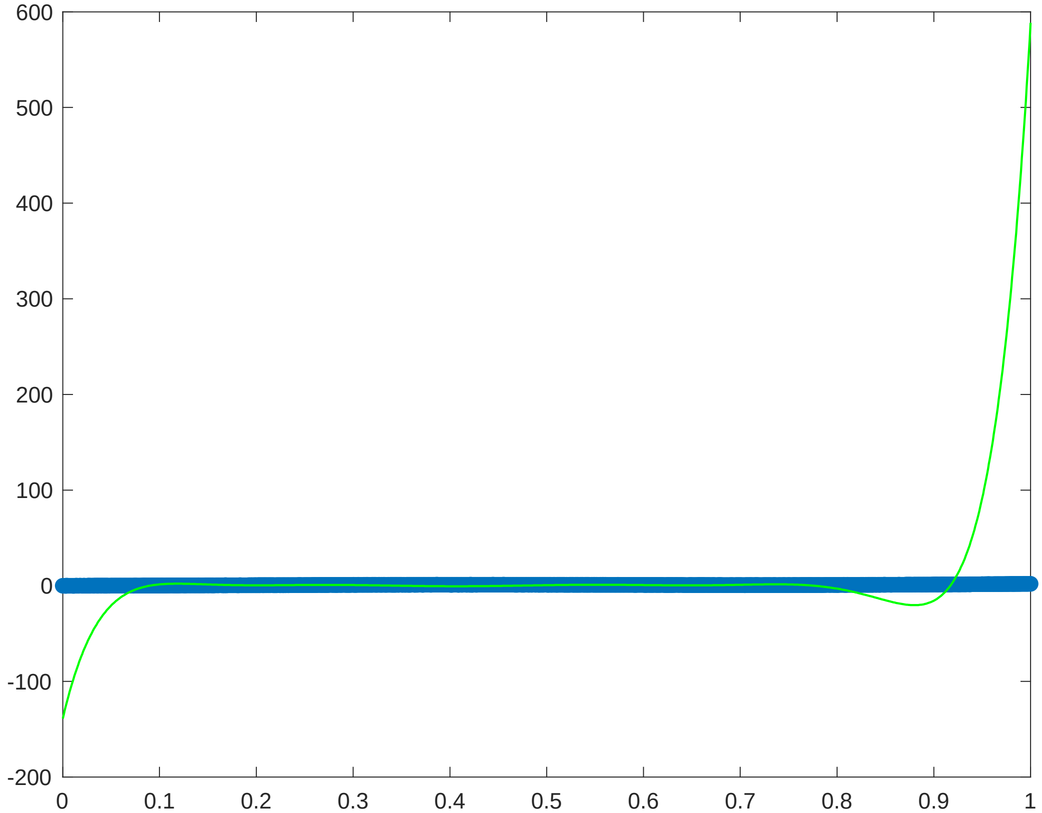


Order 10

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02/05/2020
The MSE for polynomials 2 through 10 is

| Order | MSE |
|---|---|
| 1 | 0.0352690039012964 |
| 2 | 0.0131217182624011 |
| 3 | 0.00186666077992003 |
| 4 | 0.00388046263402625 |
| 5 | 0.00485298290090212 |
| 6 | 0.923708713562784 |
| 7 | 0.238856546235134 |
| 8 | 19.4359383673695 |
| 9 | 25.5535558185329 |

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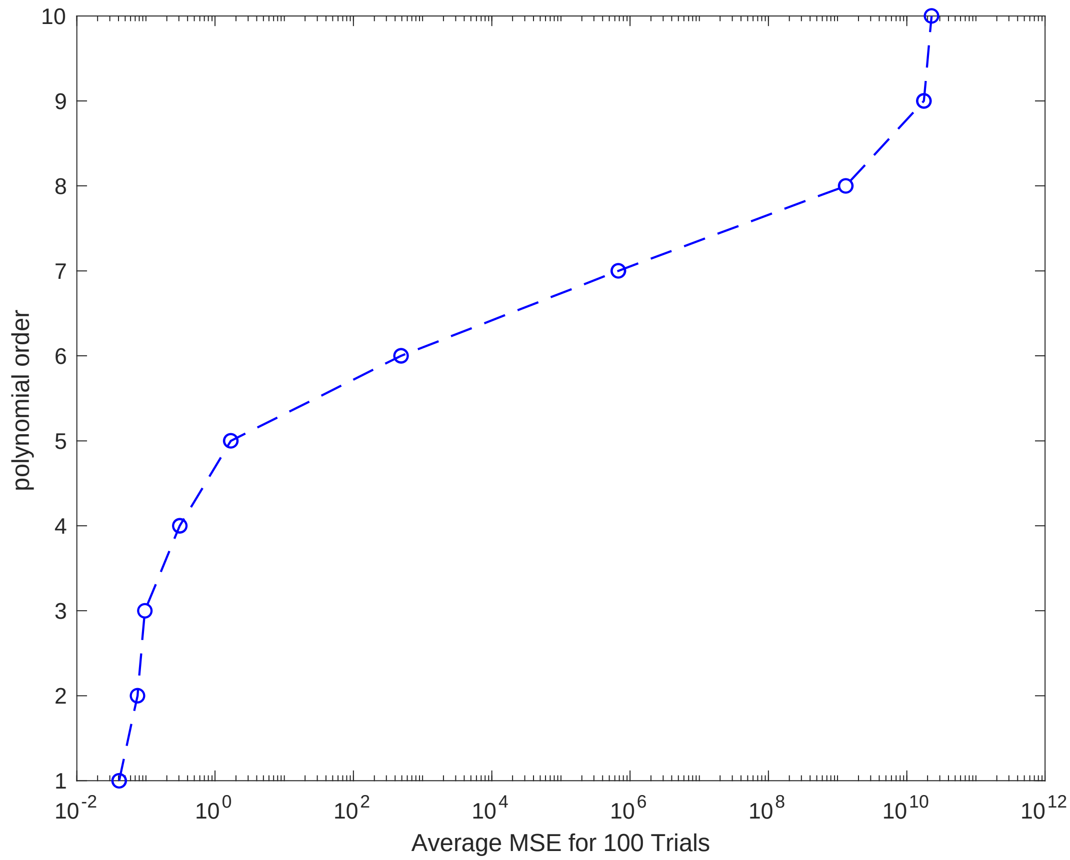
02/05/2020
**Part 3 and 4:**




Training set of 10

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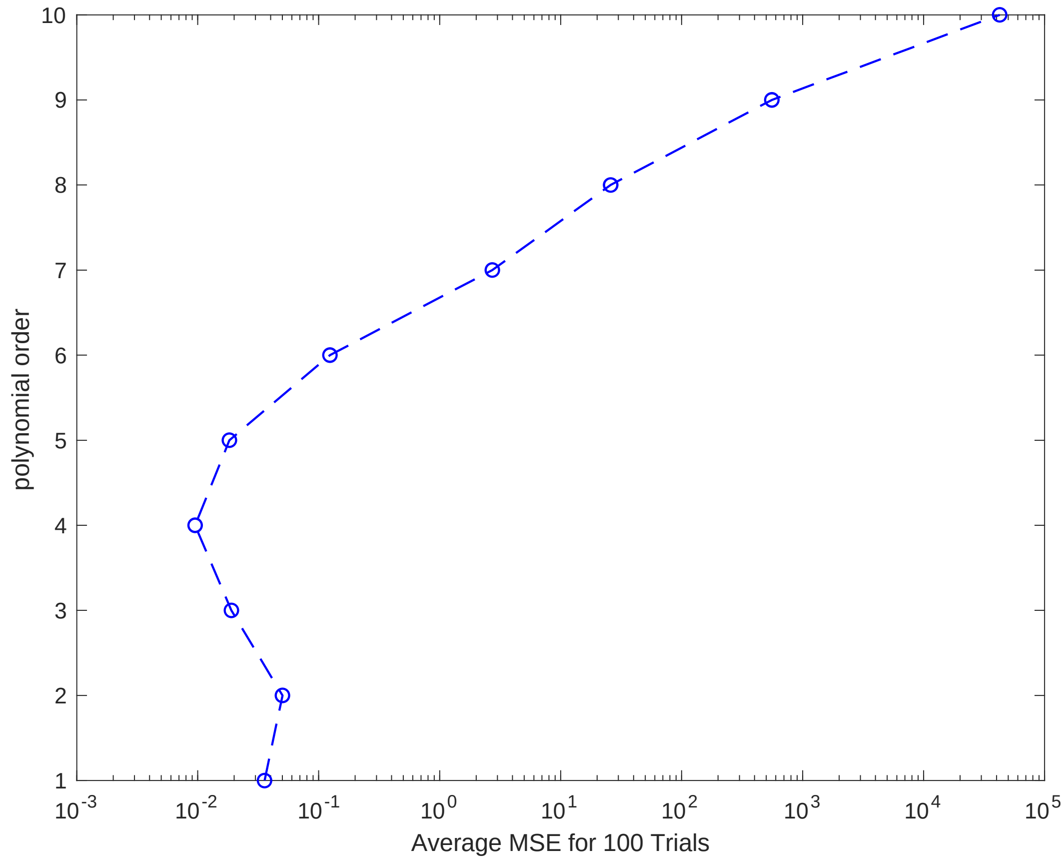


Training set of 15

Assignment 1
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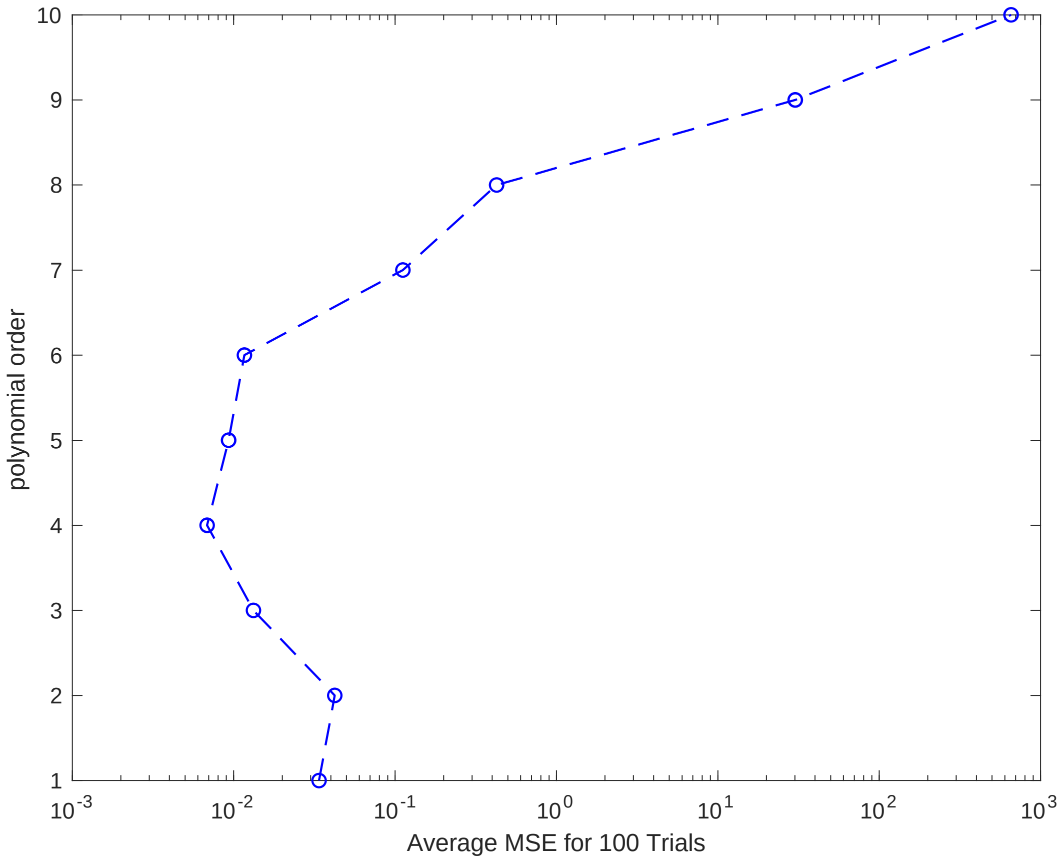


Training set of 20

Assignment 1
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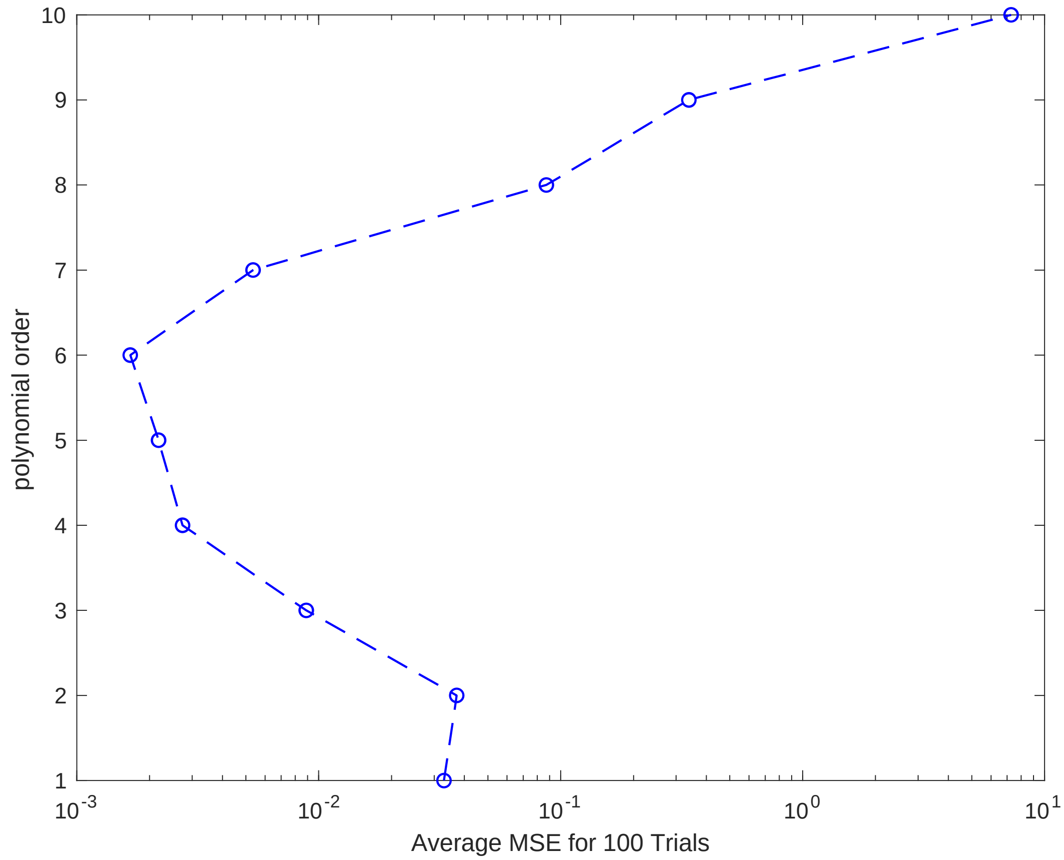


Training set of 25

Assignment 1
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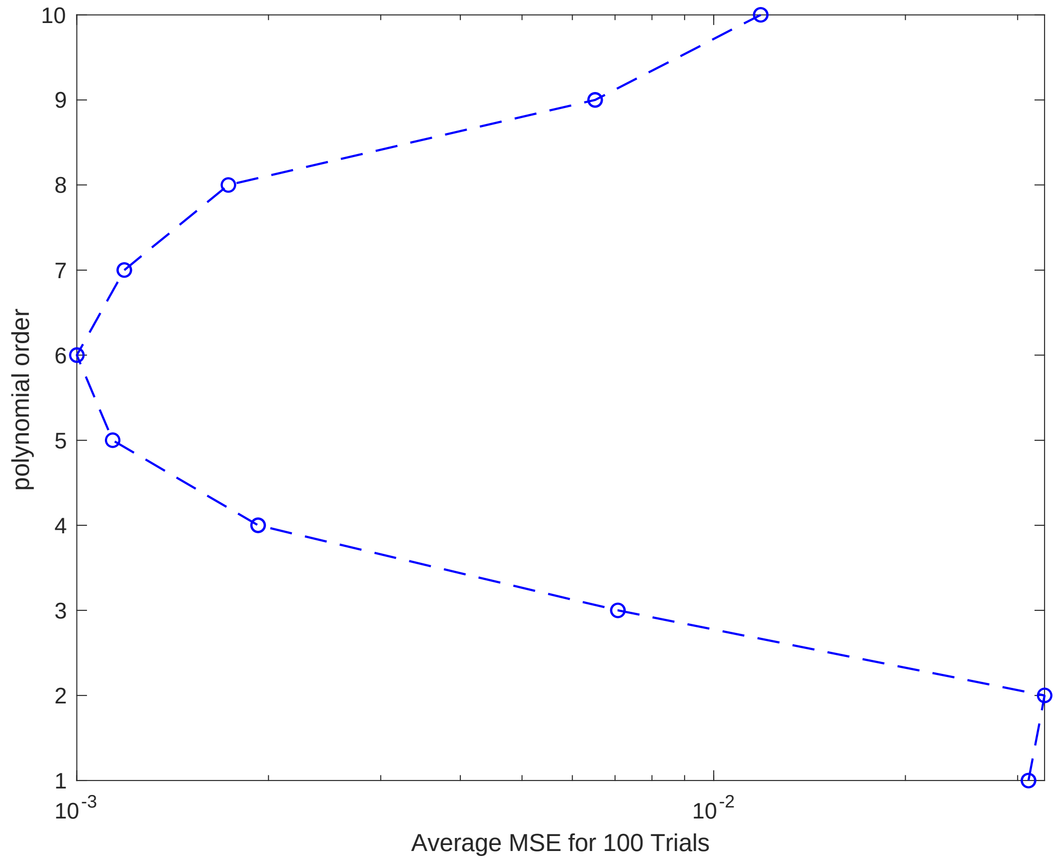


Training set of 50

Assignment 1
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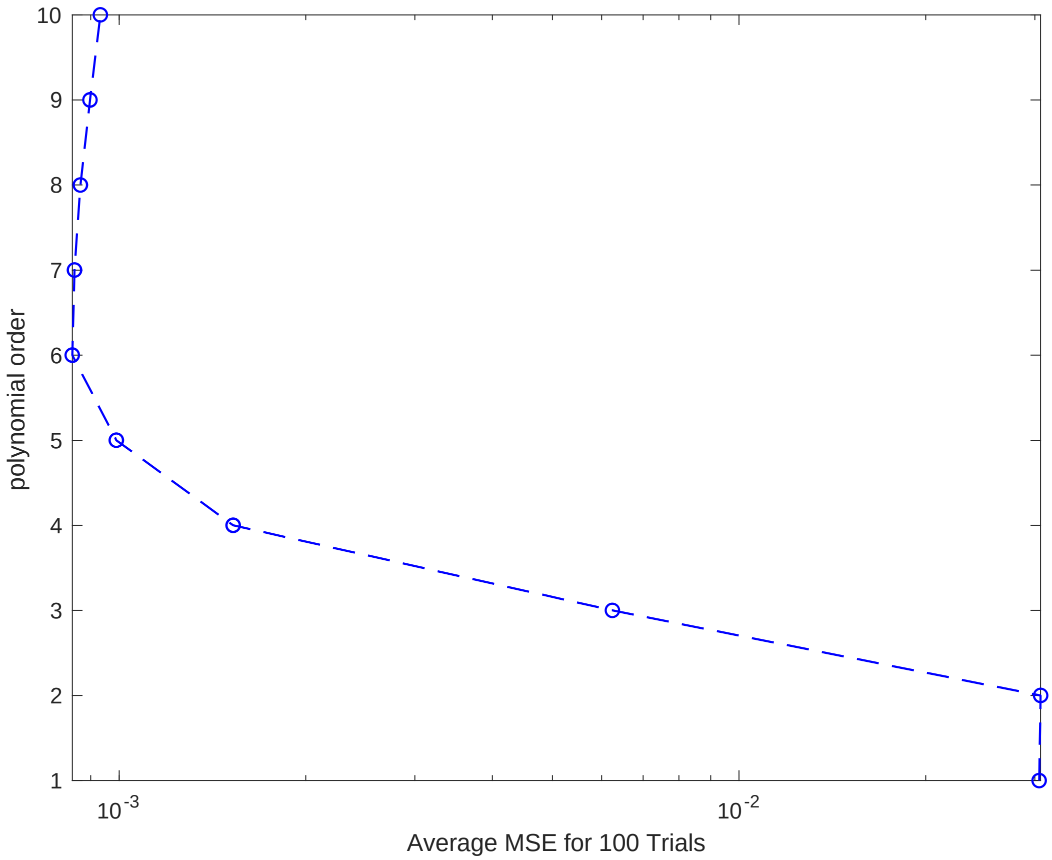


Training set of 100

Assignment 1
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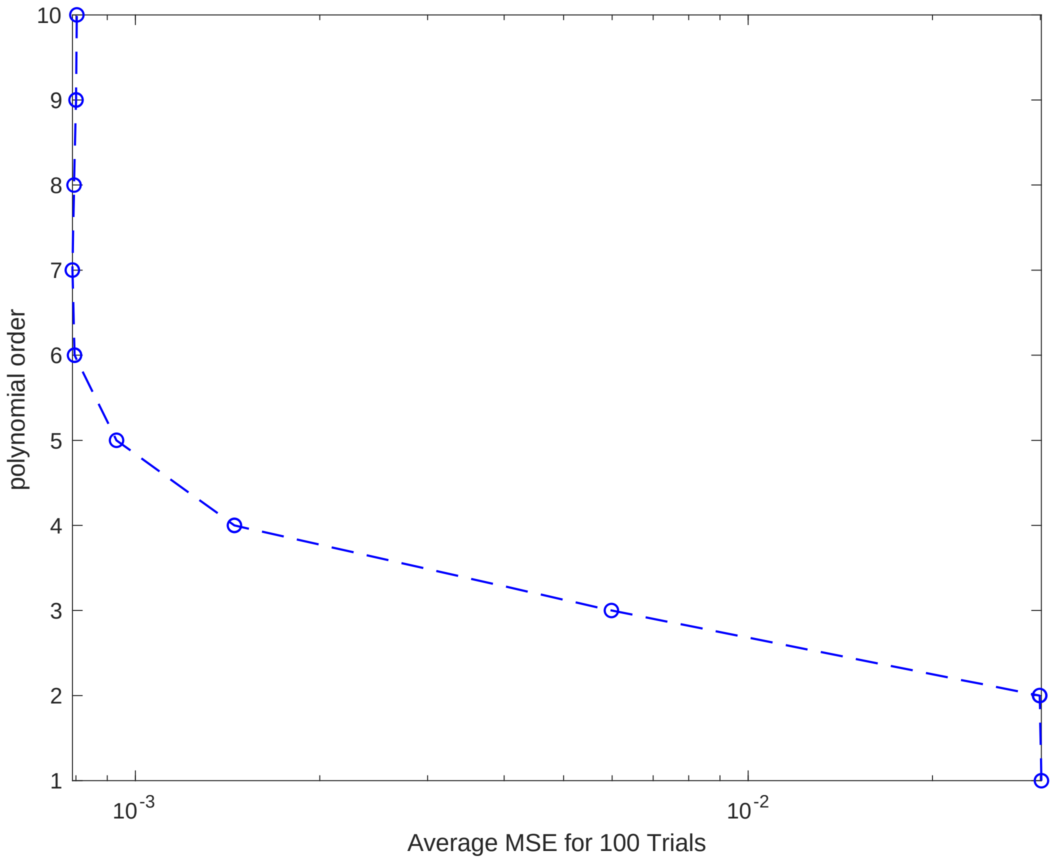


Training set of 200

The log-MSE of the model clearly changes as a function of polynomial order and number of samples used to train the model. It can be seen from the figures that as the size of training data increases, the higher order polynomials preform significantly better (have a lower log-MSE) than the lower order polynomials. However, in small training sets the lower order polynomials preform better, this is due to the fact that the higher order polynomials are simply badly conditioned when they are forced to fit to a smaller set of data points. Thus the behavior of the log-MSE makes a lot of sense according to the graphs generated.

**Part 5:**

The main point of this problem is to show that complexity, that is, higher order polynomials, is not always better. Depending on the amount of data, a person needs to be careful when generating an approximation. This problem will definitely be useful in the future when a model is needed to approximate the data.

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020
**<u>Appendix:</u>**

***Problem 1 Parts 1&2:***

```
%aspectratio code seperates the screw
clear all
clc
close all
images=dir('*.jpg');
AR=zeros();
maximum=zeros();
difference=zeros(1,length(images));
ratio=zeros(1,length(images));
ratio2=zeros(1,length(images));
for i=1:length(images)
    images=dir('*.jpg');
    images=images(i,:);
    A=imread(images.name);
    G=rgb2gray(A);
    BW = imbinarize(G);
    BW1=imcomplement(BW);
    BW2 = imfill(BW1,'holes');
    BW11=imresize(BW1, [128 128]);
    BW22=imresize(BW2, [128 128]);
    CBW=imcomplement(BW);
    AX=regionprops(CBW,'MajorAxisLength','MinorAxisLength');
    for k=1:length(AX);
        maxmajor(k)=AX(k).MajorAxisLength;
        maxminor(k)=AX(k).MinorAxisLength;
    end
    MA=max(maxmajor);
    MI=max(maxminor);
    AR(i)=MA/MI;
    difference(i)=sum(BW22(:))-sum(BW11(:));
    %the difference algorithm seperates the brackets away from the washers
and nuts by closing the
    %hole in the image and taking the binary difference
    BW2=imresize(BW, [64 64]);
    J=imcrop(BW2,[30 30 4 4]);
    numberOfWhitePixels = sum(J(:));
    numberOfBlackPixels = numel(BW) - numberOfWhitePixels;
    ratio(i) = numberOfBlackPixels/numberOfWhitePixels;
    %ratio seperates washers and nuts from the rest
    halfpic(CBW);
    [bp1,bp2]=halfpic(CBW);
    ratio2(i)=bp1/bp2;
    %ratio2 implements a function taken from an online source and compares
    %the left half and right half of the images, the idea is that washers
    %are more symmetric than nuts on average due to the fact that the
    %washers are circular and nuts tend to be hexagonal
end


subplot(4,4,1)
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

```
hold on
scatter(AR(1:10),AR(1:10),'red','fill')
scatter(AR(11:20),AR(11:20),'blue','fill')
scatter(AR(21:30),AR(21:30),'green','fill')
scatter(AR(31:40),AR(31:40),'cyan','fill')
legend('bracket','nut','screw','washer','fill')
ylabel('feature 1 aspect ratio')
title('feature 1 aspect ratio')
subplot(4,4,2)
hold on
scatter(difference(1:10),AR(1:10),'red','fill')
scatter(difference(11:20),AR(11:20),'blue','fill')
scatter(difference(21:30),AR(21:30),'green','fill')
scatter(difference(31:40),AR(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
title('feature 2 difference')
hold off
subplot(4,4,3)
hold on
scatter(difference(1:10),ratio(1:10),'red','fill')
scatter(difference(11:20),ratio(11:20),'blue','fill')
scatter(difference(21:30),ratio(21:30),'green','fill')
scatter(difference(31:40),ratio(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
title('feature 3 ratio')
hold off
subplot(4,4,4)
hold on
scatter(ratio2(1:10),AR(1:10),'red','fill')
scatter(ratio2(11:20),AR(11:20),'blue','fill')
scatter(ratio2(21:30),AR(21:30),'green','fill')
scatter(ratio2(31:40),AR(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
title('feature 4 ratio2')
hold off
subplot(4,4,5)
hold on
scatter(AR(1:10),difference(1:10),'red','fill')
scatter(AR(11:20),difference(11:20),'blue','fill')
scatter(AR(21:30),difference(21:30),'green','fill')
scatter(AR(31:40),difference(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
ylabel('feature 2 difference')
hold off
subplot(4,4,6)
hold on
scatter(difference(1:10),difference(1:10),'red','fill')
scatter(difference(11:20),difference(11:20),'blue','fill')
scatter(difference(21:30),difference(21:30),'green','fill')
scatter(difference(31:40),difference(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,7)
hold on
scatter(ratio(1:10),difference(1:10),'red','fill')
scatter(ratio(11:20),difference(11:20),'blue','fill')
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

```
scatter(ratio(21:30),difference(21:30),'green','fill')
scatter(ratio(31:40),difference(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,8)
hold on
scatter(ratio2(1:10),difference(1:10),'red','fill')
scatter(ratio2(11:20),difference(11:20),'blue','fill')
scatter(ratio2(21:30),difference(21:30),'green','fill')
scatter(ratio2(31:40),difference(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
subplot(4,4,9)
hold on
scatter(AR(1:10),ratio(1:10),'red','fill')
scatter(AR(11:20),ratio(11:20),'blue','fill')
scatter(AR(21:30),ratio(21:30),'green','fill')
scatter(AR(31:40),ratio(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
ylabel('feature 3 ratio')
hold off
subplot(4,4,10)
hold on
scatter(difference(1:10),ratio(1:10),'red','fill')
scatter(difference(11:20),ratio(11:20),'blue','fill')
scatter(difference(21:30),ratio(21:30),'green','fill')
scatter(difference(31:40),ratio(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,11)
hold on
scatter(ratio(1:10),ratio(1:10),'red','fill')
scatter(ratio(11:20),ratio(11:20),'blue','fill')
scatter(ratio(21:30),ratio(21:30),'green','fill')
scatter(ratio(31:40),ratio(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,12)
hold on
scatter(ratio2(1:10),ratio(1:10),'red','fill')
scatter(ratio2(11:20),ratio(11:20),'blue','fill')
scatter(ratio2(21:30),ratio(21:30),'green','fill')
scatter(ratio2(31:40),ratio(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,13)
hold on
scatter(AR(1:10),ratio2(1:10),'red','fill')
scatter(AR(11:20),ratio2(11:20),'blue','fill')
scatter(AR(21:30),ratio2(21:30),'green','fill')
scatter(AR(31:40),ratio2(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
ylabel('feature 4 ratio2')
hold off
subplot(4,4,14)
hold on
scatter(difference(1:10),ratio2(1:10),'red','fill')
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

```
scatter(difference(11:20),ratio2(11:20),'blue','fill')
scatter(difference(21:30),ratio2(21:30),'green','fill')
scatter(difference(31:40),ratio2(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,15)
hold on
scatter(ratio(1:10),ratio2(1:10),'red','fill')
scatter(ratio(11:20),ratio2(11:20),'blue','fill')
scatter(ratio(21:30),ratio2(21:30),'green','fill')
scatter(ratio(31:40),ratio2(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
subplot(4,4,16)
hold on
scatter(ratio2(1:10),ratio2(1:10),'red','fill')
scatter(ratio2(11:20),ratio2(11:20),'blue','fill')
scatter(ratio2(21:30),ratio2(21:30),'green','fill')
scatter(ratio2(31:40),ratio2(31:40),'cyan','fill')
legend('bracket','nut','screw','washer')
hold off
```

***Problem 1 Part 3:***

```
clear all
clc
close all
images=dir('*.jpg');
HDspace=zeros(40,40);
for i=1:length(images)
    for j=1:length(images)
    images=dir('*.jpg');
    firstimage=imresize(imbinarize(rgb2gray((imread(images(i).name)))),[64
64]);
    secondimage=imresize(imbinarize(rgb2gray((imread(images(j).name)))),[64
64]);
    difference=firstimage-secondimage;
    differencepw2=difference.^2;
    pixeladdition=sqrt(sum(differencepw2(:)));
    HDspace(i,j)=pixeladdition;
%     images=images(i,:);
%     A=imread(images.name);
%     BW1=imresize(BW, [64 64]);
    end
end
figure(1)
imagesc(HDspace)
colorbar

%beginning low dimensional part
clear all
clc
images=dir('*.jpg');
AR=zeros();
maximum=zeros();
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

```
difference=zeros(1,length(images));
ratio=zeros(1,length(images));
ratio2=zeros(1,length(images));
for i=1:length(images)
    images=dir('*.jpg');
    images=images(i,:);
    A=imread(images.name);
    G=rgb2gray(A);
    BW = imbinarize(G);
    BW1=imcomplement(BW);
    BW2 = imfill(BW1,'holes');
    BW11=imresize(BW1, [128 128]);
    BW22=imresize(BW2, [128 128]);
    CBW=imcomplement(BW);
    AX=regionprops(CBW,'MajorAxisLength','MinorAxisLength');
    for k=1:length(AX);
        maxmajor(k)=AX(k).MajorAxisLength;
        maxminor(k)=AX(k).MinorAxisLength;
    end
    MA=max(maxmajor);
    MI=max(maxminor);
    AR(i)=MA/MI;
    difference(i)=sum(BW22(:))-sum(BW11(:));
    %the difference algorithm seperates the brackets away from the washers
and nuts by closing the
    %hole in the image and taking the binary difference
    BW2=imresize(BW, [64 64]);
    J=imcrop(BW2,[30 30 4 4]);
    numberOfWhitePixels = sum(J(:));
    numberOfBlackPixels = numel(BW) - numberOfWhitePixels;
    ratio(i) = numberOfBlackPixels/numberOfWhitePixels;
    %ratio seperates washers and nuts from the rest
    halfpic(CBW);
    [bp1,bp2]=halfpic(CBW);
    ratio2(i)=bp1/bp2;
    %ratio2 implements a function taken from an online source and compares
    %the left half and right half of the images, the idea is that washers
    %are more symmetric than nuts on average due to the fact that the
    %washers are circular and nuts tend to be hexagonal
end

combinedfeaturematrix=[AR', difference', ratio', ratio2'];
LDspace=zeros(40,40);
for i=1:40
    for j=1:40
        newdifference=combinedfeaturematrix(i,:)-combinedfeaturematrix(j,:)
        newdifferencepw2=newdifference.^2;
        featureaddition=sqrt(sum(newdifferencepw2(:)));
        LDspace(i,j)=featureaddition;
    end
end

figure(2)
imagesc(LDspace)
colorbar
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

### *Problem 2 All Parts:*

```
clc
clear all
close all
x=[0:1:2700];
g1=(1/(sqrt(2*pi)*300))*exp(-(x-1500).^2/(2*300^2));
g2=(1/(sqrt(2*pi)*100))*exp(-(x-500).^2/(2*100^2));
g3=(1/(sqrt(2*pi)*100))*exp(-(x-200).^2/(2*100^2));
spdf=0.35*g1+0.40*g2+0.25*g3
N=[200 20000]
for i=1:2
    a=normrnd(1500,300,[1,N(i)*0.35]);
    b=normrnd(500,100,[1,N(i)*0.40]);
    c=normrnd(200,100,[1,N(i)*0.25]);
    samples=[a,b,c];
    figure(i)
    hold on
    histogram(samples(1,:),50,'Normalization','pdf');
    plot(x,spdf,'g','LineWidth',2);
    xlabel('Weight in grams')
    ylabel('Probability')
    hold off
end
```

### *Problem 3 All Parts:*

```
clear all
clc
syms x;
pw1=9999/10000;
pw2=1/10000;
c12=1*10^6;
c21=20000;
%ML then MAP then Bayes risk
criteria=[1 pw2/pw1 (c12*pw2)/(c21*pw1)];
for i=1:3
eqn=((1/(sqrt(2*pi)*0.3))*exp(-(x)^2/(2*0.3^2)))/((1/(sqrt(2*pi)*0.1))*exp(-
(x-1)^2/(2*0.1^2))) == criteria(i);
if i==1
S1=solve(eqn,x)
elseif i==2
S2=solve(eqn,x)
else
S3=solve(eqn,x)
end
end
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020
***Problem 4 All Parts:***

```
clear all
clc
%Part(1)
[T1,T2,T3]=readvars('hw1p4_data.csv');
d1=T1(:,1);
d2=T2(:,1);
d3=T3(:,1);
figure(1)
S1=scatter(d1,d2,5,'green');
%Correlation coefficiant is defnitely positive, somewhere between 0.5 and 1
figure(2)
%Without doing any calulations it looks like the correlation coefficiant is
%almost negative 1.
S2=scatter(d1,d3,5,'red');
figure(3)
%This data set is also a negative correlation, looks to be between -0.5 and
%-1
S3=scatter(d2,d3,5,'black');

%Part(2)
C1=cov(d1,d2);
C2=cov(d1,d3);
C3=cov(d2,d3);
sigma1=sqrt(C1(1,1));
sigma2=sqrt(C1(2,2));
sigma3=sqrt(C2(2,2));
%Correlation Coffeiciant Between first and second columns
ro12=C1(1,2)/(sigma1*sigma2);
%Correlation Coffeiciant Between first and third columns
ro13=C2(1,2)/(sigma1*sigma3);
%Correlation Coffeiciant Between second and third columns
ro23=C3(1,2)/(sigma2*sigma3);

%Yes the off diagonal terms are in agreement from what we see in the scatter
plots!

mu=[mean(T1) mean(T2) mean(T3)];

%Part(3)and(4)


newdata1=mvnrnd(mu(1,(1:2)),C1,length(d1));

newdata2=mvnrnd([mu(1,1) mu(1,3)],C2,length(d1));

newdata3=mvnrnd(mu(1,(2:3)),C3,length(d1));

figure(4)
hold on
scatter(newdata1(:,1),newdata1(:,2),'+','cyan')
scatter(d1,d2,5,'green');
hold off
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

```
figure(5)
hold on
scatter(newdata2(:,1),newdata2(:,2),'+','cyan')
scatter(d1,d3,5,'red');
hold off
figure(6)
hold on
scatter(newdata3(:,1),newdata3(:,2),'+','cyan')
scatter(d2,d3,5,'black');
hold off

%The scatter plots are very similar to those generated with the data
%samples, the only difference now is that the data is gaussian, so the
%scatter plot is no longer skewed as it is before

%Part(5)
```

***Problem 5 Part 1:***

```
clear all
clc
[X1,X2]=readvars('hw1p5_data.csv');
data=[X1 X2];
n=10
y=datasample(data,n)
y1=y(:,1);
y2=y(:,2);
polynomial=polyfit(y1,y2,1);
Pval=polyval(polynomial,X1);
err1=immse(data,[X1,Pval])
figure(1)
plot(X1,X2,'o',X1,Pval,'green','LineWidth',1)
title('part 1, polynomial of order 1')
xlabel('X1')
ylabel('X2')
```

***Problem 5 Part 2:***

```
clear all
clc
[X1,X2]=readvars('hw1p5_data.csv');
data=[X1 X2];
n=10
y=datasample(data,n)
y1=y(:,1);
y2=y(:,2);
polynomial=polyfit(y1,y2,1);
Pval=polyval(polynomial,X1);
err1=immse(data,[X1,Pval])
figure(1)
plot(X1,X2,'o',X1,Pval,'green','LineWidth',1)
title('part 1, polynomial of order 1')
```

Assignment 1
Mahmood Mustafa Shilleh
02/05/2020

```
xlabel('X1')
ylabel('X2')
vec=zeros(9,1)
for i=2:10
        polynomial=polyfit(y1,y2,i);
        Pval=polyval(polynomial,X1);
        figure(i)
        plot(X1,X2,'o',X1,Pval,'green','LineWidth',1)
        grid on
        err1=immse(data,[X1,Pval]);
        vec(i-1)=err1
    end
```

***Problem 5 Part 3 and 4:***

```
clear all
clc
%Part(1)
[X1,X2]=readvars('hw1p5_data.csv');
data=[X1 X2];
n=[10 15 20 25 50 100 200];
vec=zeros(100,10);
%vec2=zeros(10,100)
G=zeros(7,10);
for k=1:7
for j=1:100
y=datasample(data,n(k));
y1=y(:,1);
y2=y(:,2);
    for i=1:10
        polynomial=polyfit(y1,y2,i);
        Pval=polyval(polynomial,X1);
        %figure(i)
        %plot(X1,X2,'o',X1,Pval,'green')
        %grid on
        err1=immse(data,[X1,Pval]);
        vec(j,i)=err1;
    end
end
G(k,:)=mean(vec)
end
for Q=1:7
    figure(Q)
semilogx(G(Q,:),1:10,'b--o','LineWidth',1)
xlabel('Average MSE for 100 Trials')
ylabel('polynomial order')
end
```