

Stoch Proj 3

1. $f(x, \lambda) = \lambda e^{-\lambda x}$

Exponential

$$L(\lambda, \vec{x}) = \prod_{i=1}^n f(x_i, \lambda) \quad \text{where } \vec{x} = (x_1, \dots, x_n)$$

$$= \prod_{i=1}^n \lambda e^{-\lambda x_i}$$

$$= \lambda^n \exp\left(-\lambda \sum_{i=1}^n x_i\right)$$

$$\ln(L(\lambda, \vec{x})) = \ln\left(\lambda^n \exp\left(-\lambda \sum_{i=1}^n x_i\right)\right)$$

$$= \ln(\lambda^n) - \lambda \sum_{i=1}^n x_i$$

$$\frac{d \ln(L(\lambda, \vec{x}))}{d\lambda} = \frac{n}{\lambda} - \sum_{i=1}^n x_i = 0$$

$$\Rightarrow \lambda = \frac{n}{\sum_{i=1}^n x_i}$$

Rayleigh

$$f(x, \lambda) = \frac{x}{\lambda^2} \exp\left(-\frac{1}{2} \cdot \left(\frac{x}{\lambda}\right)^2\right)$$

$$L(\lambda, \vec{x}) = \prod_{i=1}^n \frac{x_i}{\lambda^2} \exp\left(-\frac{1}{2} \cdot \left(\frac{x_i}{\lambda}\right)^2\right) \quad \text{where } \vec{x} = (x_1, \dots, x_n)$$

$$= \frac{1}{\lambda^{2n}} \cdot \prod_{i=1}^n x_i \cdot \exp\left(-\frac{1}{2} \lambda^2 \sum_{i=1}^n x_i^2\right)$$

$$\ln(L(\lambda, \vec{x})) = \ln\left(\prod_{i=1}^n x_i\right) - \ln(\lambda^{2n}) - \frac{1}{2} \lambda^2 \sum_{i=1}^n x_i^2$$

$$= \ln\left(\prod_{i=1}^n x_i\right) - 2n \ln(\lambda) - \frac{1}{2} \lambda^2 \sum_{i=1}^n x_i^2$$

$$\frac{d \ln(L(\lambda, \vec{x}))}{d\lambda} = 0 = -\frac{2n}{\lambda} + \frac{1}{\lambda^3} \sum_{i=1}^n x_i^2 = 0$$

$$2n\lambda^2 = \sum_{i=1}^n x_i^2$$

$$\lambda = \sqrt{\frac{\sum_{i=1}^n x_i^2}{2n}}$$

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Stoch Proj 3

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Part 2

```
clear all;close all;clc

%Implemented max likelihood estimates for lambda
estExp = @(data) max(size(data))/sum(data,'all');
estRay = @(data) sqrt(sum(data.^2,'all')/(2*max(size(data))));

N = 1000; % number of random variables
N_obs = 70;
lambda = 1;
% random draws from exponential and Rayleigh distribution
x_exp = exprnd(lambda,[N,N_obs]);
x_ray = raylrnd(lambda,[N,N_obs]);

lambdaexp_est = zeros(N_obs,1);
lambdaray_est = zeros(N_obs,1);
MSE_exp = zeros(N_obs,1);
MSE_ray = zeros(N_obs,1);
bias_exp = zeros(N_obs,1);
bias_ray = zeros(N_obs,1);
% loop to calculate lambda estimate, MSE, and bias for each number of
% observations
for ii = 1:N_obs
    lambdaexp_est(ii) = estExp(x_exp(:,ii));
    lambdaray_est(ii) = estRay(x_ray(:,ii));
    MSE_exp(ii) = mean((lambdaexp_est(1:ii)-lambda).^2);
    MSE_ray(ii) = mean((lambdaray_est(1:ii)-lambda).^2);
    bias_exp(ii) = mean(lambdaexp_est(1:ii))-lambda;
    bias_ray(ii) = mean(lambdaray_est(1:ii))-lambda;
end
% final lambda estimate is the mean of the estimates of all
% observations
lambdahat_exp = mean(lambdaexp_est);
lambdahat_ray = mean(lambdaray_est);

var_exp = zeros(N_obs,1);
var_ray = zeros(N_obs,1);
for ii = 1:N_obs
```

```

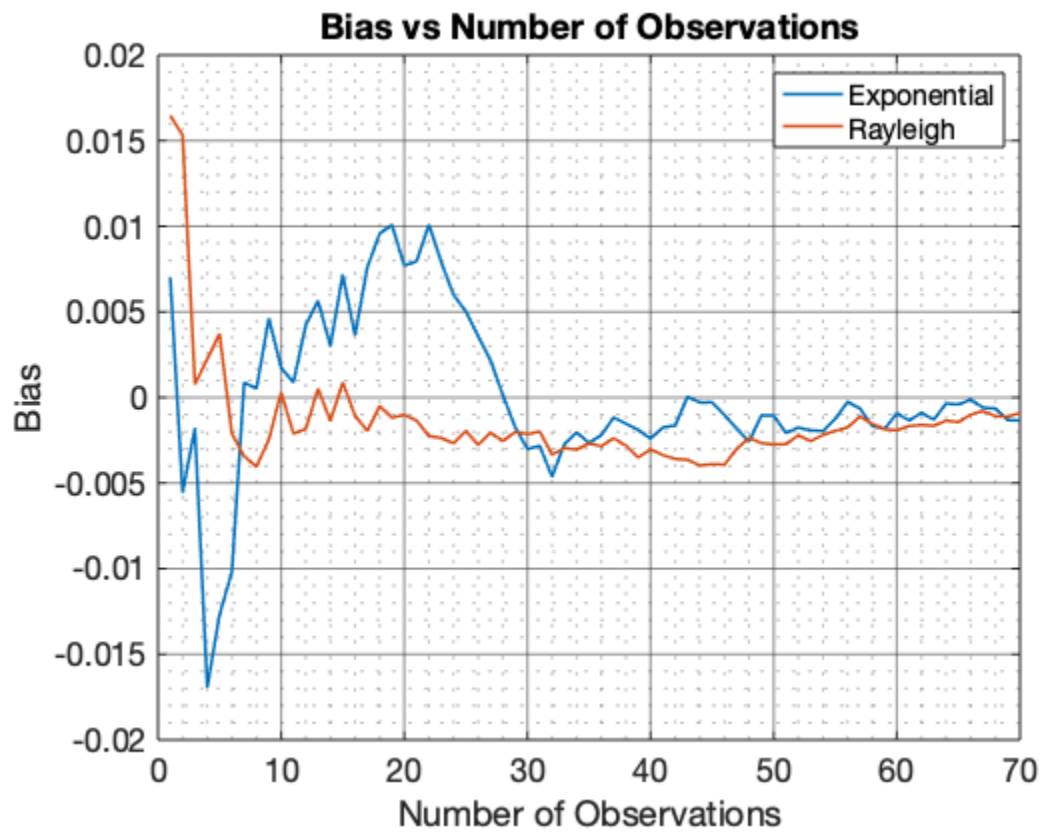
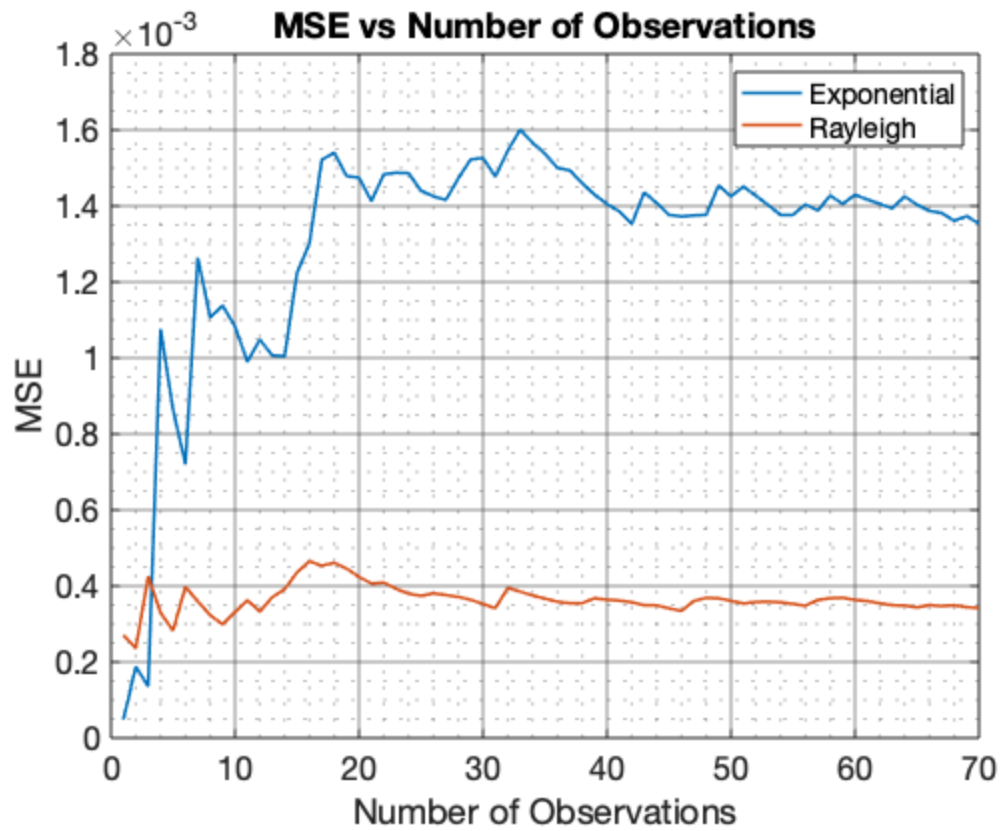
        var_exp(ii) = abs(mean((lambdahat_exp-
mean(lambdaexp_est(1:ii)).^2)));
        var_ray(ii) = abs(mean((lambdahat_ray-
mean(lambdaray_est(1:ii)).^2)));
    end

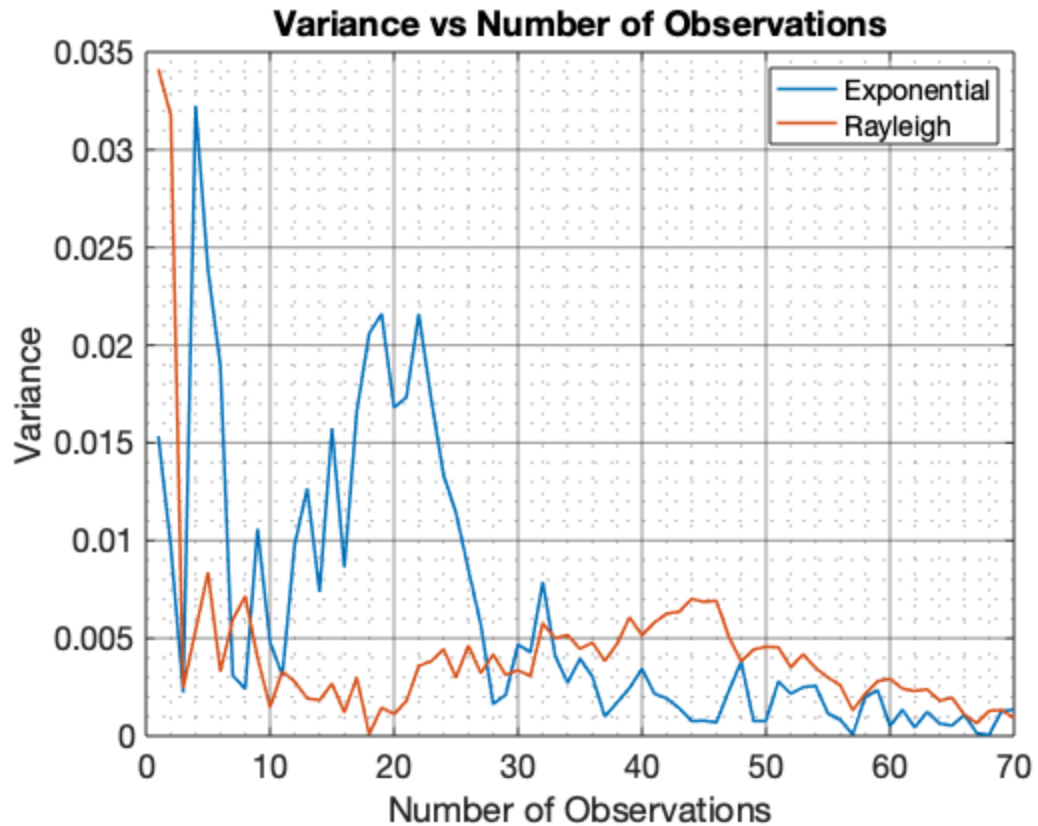
%plotting MSE, bias, and variance
figure
plot(1:N_obs,MSE_exp,1:N_obs,MSE_ray, 'LineWidth', 1.5)
title('MSE vs Number of Observations','FontSize', 16)
xlabel('Number of Observations', 'FontSize', 14)
ylabel('MSE', 'FontSize', 14)
grid on;
grid minor
ax = gca;
ax.GridAlpha = 0.5;
ax.FontSize = 16;
legend('Exponential','Rayleigh', 'FontSize', 14)

figure
plot(1:N_obs,bias_exp,1:N_obs,bias_ray, 'LineWidth', 1.5)
title('Bias vs Number of Observations','FontSize', 16)
xlabel('Number of Observations', 'FontSize', 14)
ylabel('Bias', 'FontSize', 14)
grid on;
grid minor
ax = gca;
ax.GridAlpha = 0.5;
ax.FontSize = 16;
legend('Exponential','Rayleigh', 'FontSize', 14)

figure
plot(1:N_obs,var_exp,1:N_obs,var_ray, 'LineWidth', 1.5)
title('Variance vs Number of Observations','FontSize', 16)
xlabel('Number of Observations', 'FontSize', 14)
ylabel('Variance', 'FontSize', 14)
grid on;
grid minor
ax = gca;
ax.GridAlpha = 0.5;
ax.FontSize = 16;
legend('Exponential','Rayleigh', 'FontSize', 14)

```





Part 3

```
%loading the data
data = load( 'data.mat' );
data = data.data;

%We derived the ML estimates earlier, but here is a shorthand
  derivation
%just in case:

% Exponential:
% f(x,lambda) = lambda*e^-lambda*x  x nonnegative
%              0 else

% L(lambda) = L(lambda;x1,x2,...,xn) = Product_j(f(xj;lambda)
%              = lambda^n*exp(-lambda[SUM_j(xj)])
%Taking log an finding max
%      l(lambda) = n*log(lambda) -lambda*SUM_j(xj)
%      dl(lambda)/dlambda = n/lambda - SUM_j(xj) = 0
%      => lambda = n/SUM_j(xj)

% Rayleigh
% f(x,lambda) = x/lambda^2 * exp(-x^2/(2*lambda^2))      x nonnegative
```

```

% L(lambda) = PROD_j(xj)/(lambda^2n)*exp(-1/2*SUM((xj/lambda)^2)
% Taking log:
% l(lambda) = log(sum_j(xj))-2nlog(lambda)-1/2^n*SUM_j((xj/lambda)^2)
% dl(lambda)/dlambda = -2n/lambda + SUM_j(xj^2/lambda^3) = 0
%      => lambda = sqrt(SUM_j(xj^2)/2n)

%Computing the maximum likelihood estimates for the data provided
lambda_exp = estExp(data);
lambda_ray = estRay(data);

%Plugging in to the likelihood functions (log likelihood) to determine
%which distribution we have:
l_exp = @(data,lambda,n) (n*log(lambda) - lambda*sum(data,'all'));
l_ray = @(data,lambda,n)
    log(prod(data,'all'))-2*n*log(lambda)-0.5*sum((data./
lambda).^2,'all');

%size of input
n = max(size(data));

%checking the likelihoods
Likely_exp = l_exp(data,lambda_exp,n)
Likely_ray = l_ray(data,lambda_ray,n)

```

Comments on Results

The data was most likely from an exponential distribution. We note that the -inf likelihood for the rayleigh distribution is most likely due to machine errors when taking the product of all the elements of the data (machine mistakes the product as zero, yielding a log of -inf, whereas the product is not exactly zero).

```

Likely_exp =

    1.0535e+03

```

```

Likely_ray =

    -Inf

```

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