MODULE 6:
CHALLENGE PROBLEM
Scenario Analysis

- **Challenge**
  - **Perform convergence, sensitivity and epistemic uncertainty analyses for several scenarios as instructed.**

- Skills
  - Reading in data
  - Performing convergence analysis
  - Calculating epistemic quantiles
  - Determining sensitive inputs
  - Generating output plots
  - Comparing results from scenarios

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OVERVIEW OF CHALLENGE PROBLEM

- For the Challenge problem, we will be looking at results from several different scenarios

Scenario	Initiation	Growth	Flaw Orientation	Mitigation	
				Type	Timing
Scenario 1	Initial Flaw	Fatigue	Circumferential	None	---
Scenario 2	PWSCC	PWSCC	Circumferential	None	---
Scenario 3	PWSCC	PWSCC	Circumferential & Axial	None	---
Scenario 4	PWSCC	PWSCC	Circumferential & Axial	MSIP	20 Years
Scenario 5	PWSCC	PWSCC	Circumferential & Axial	MSIP	40 Years
Scenario 6	PWSCC	PWSCC	Circumferential & Axial	Zn	20 Years
Scenario 7	PWSCC	PWSCC	Circumferential & Axial	H2	20 Years
Scenario 8	PWSCC	PWSCC	Circumferential & Axial	Zn & H2	20 Years
Scenario 9	PWSCC	PWSCC	Circumferential & Axial	Inlay	40 Years
Scenario 10	PWSCC & Fatigue	PWSCC & Fatigue	Circumferential & Axial	MSIP, Zn, & H2	20 Years
Scenario 11	Fatigue	Fatigue	Circumferential & Axial	None	---

Next

- For the Challenge problem, we will be looking at results from several different scenarios

Scenario	Initiation	Growth	Flaw Orientation	Mitigation	
				Type	Timing
Scenario 1	Initial Flaw	Fatigue	Circumferential	None	---
Scenario 2	PWSCC	PWSCC	Circumferential	None	---
Scenario 3	PWSCC	PWSCC	Circumferential & Axial	None	---
Scenario 4	PWSCC	PWSCC	Circumferential & Axial	MSIP	20 Years
Scenario 5	PWSCC	PWSCC	Circumferential & Axial	MSIP	40 Years
Scenario 6	PWSCC	PWSCC	Circumferential & Axial	Zn	20 Years
Scenario 7	PWSCC	PWSCC	Circumferential & Axial	H2	20 Years
Scenario 8	PWSCC	PWSCC	Circumferential & Axial	Zn & H2	20 Years
Scenario 9	PWSCC	PWSCC	Circumferential & Axial	Inlay	40 Years
Scenario 10	PWSCC & Fatigue	PWSCC & Fatigue	Circumferential & Axial	MSIP, Zn, & H2	20 Years
Scenario 11	Fatigue	Fatigue	Circumferential & Axial	None	---

Next

CHALLENGE PROBLEM GOALS

- The goals for the challenge problem are to:
  - Find a converged solution for a given scenario
  - Perform a sensitivity analysis on the converged solution
  - Calculate epistemic quantiles for the converged solution
  - Compare the results from different scenarios
- All xLPR results for each scenario have already been generated.

Next

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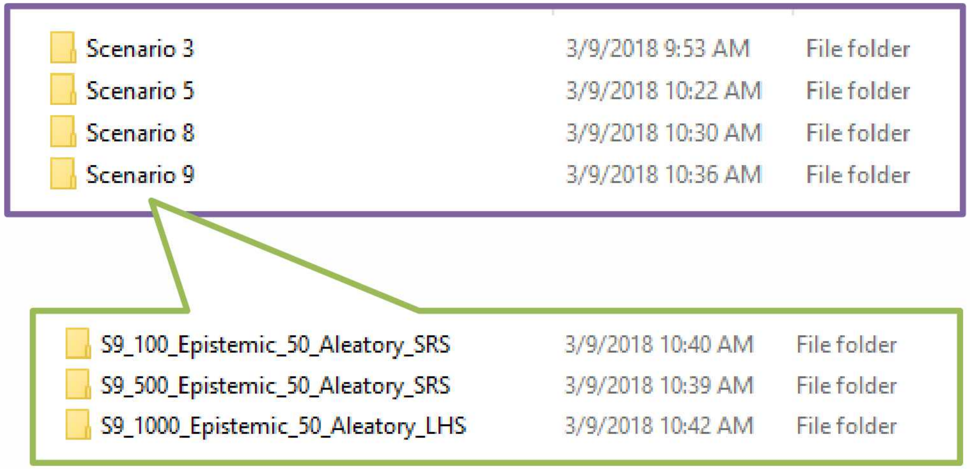
- Navigate to **Exercises/Challenge Problems**.

There are 4 scenario folders



Within each scenario, there are folders containing the sampled inputs and results for the following sample sizes:

- 100 Epistemic, 50 Aleatory
- 500 Epistemic, 50 Aleatory
- 1000 Epistemic, 50 Aleatory

Some runs use SRS, while others use LHS.

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- Open **Exercises/Challenge Problems/Scenario_Analysis_Results.xlsx**.
- This file contains a table to record the results of the challenge problem. Make sure to fill out the table as you work through the problem.

Scenario Analysis Results				
	Scenario 3	Scenario 5	Scenario 8	Scenario 9
Description of Scenario				
CI Width for 100 Samples				
CI Width for 500 Samples				
CI Width for 1000 Samples				
Number of Samples in Converged Solution				
Sampling Scheme in Converged Solution				
Sample Mean				
Bootstrap CI				
Sensitivity Analysis Model				
Sensitivity Analysis R2				
Top 3 Important Variables				
95th Quantile				
50th Quantile				
5th Quantile				

Next

- Open R Studio and set your working directory to **Exercises/Challenge Problems/Scenario 3**
- Open an R script and save it as “Scenario_3.R”
- Open **S3_100_Epistemic_50_Aleatory_SRS/ S3_Simulation_Results_100E_50A_SRS.xlsx** and notice how the data doesn’t start until the 5th row.

What sheet contains the results for Occurrence of Circumferential Rupture?

Answer

Next

- Read in the occurrence of circumferential rupture results from the run with **100 epistemic and 50 aleatory SRS** samples and save it to a variable called **dat**.
- Make sure to set *startRow* = 5 so that only the data is read in.

How

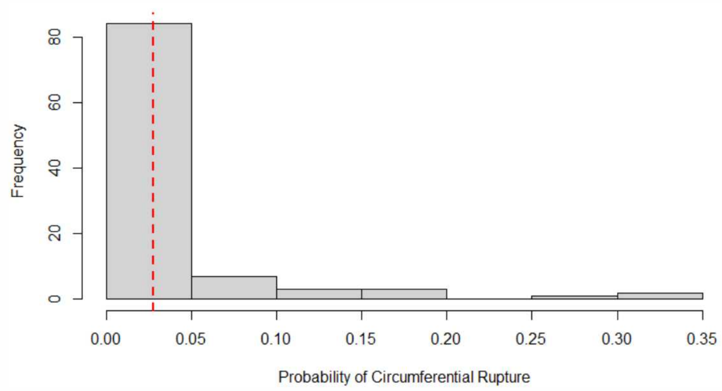
Next

- Select the row of **dat** where the first column = 60 and save this to a variable called **ep100**.
- Remove the first element of **ep100** that contains the year.
- Change **ep100** to a numeric vector.

How

Next

- Plot a histogram of the **ep100** with a vertical line at the mean.



What is the mean probability of occurrence of circumferential rupture using 100 epistemic samples?

Answer

How

Next

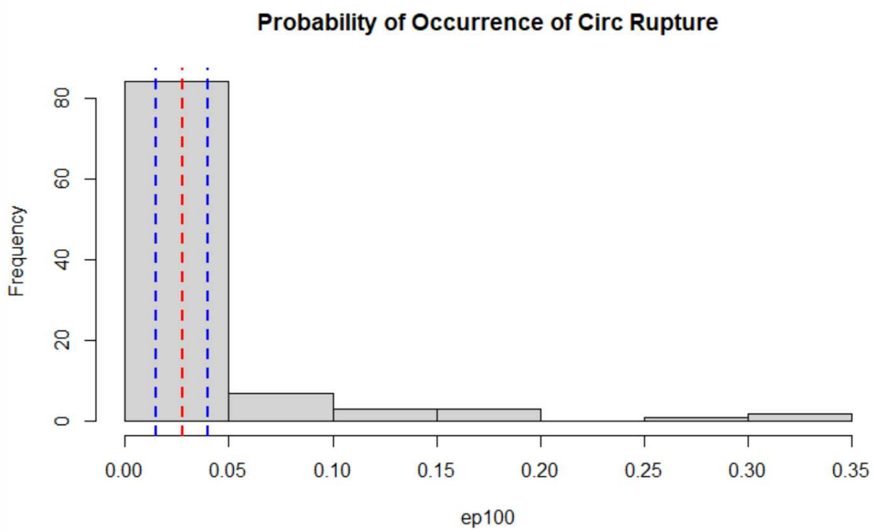
- Perform a bootstrap for the mean probability of occurrence of rupture using 1000 samples. Make sure to save the bootstrap means to a vector.

How

Next

SCENARIO 3 CONVERGENCE ANALYSIS 100 SAMPLES

- Calculate a 95% basic confidence interval for the mean. Save the lower and upper bounds as **lb100** and **ub100**, respectively.
- Plot the confidence interval as blue, dashed, vertical lines on histogram of **ep100**.
- Plot the sample mean as a red, dashed, vertical line.
- Save your figure.



How

Next

SCENARIO 3 CONVERGENCE ANALYSIS 100 SAMPLES

- Calculate the width of your confidence interval by subtracting your lower bound from your upper bound. Save this to a variable called **ciWidth100**.
- For this example, we will consider a QoI to be converged if the confidence interval width is less than 0.01.

How wide is your confidence interval?
What does this tell you?

Answer

How

Next

- This too much sampling uncertainty for our application since the CI width is greater than 0.01.

How can we reduce the amount of sampling uncertainty?

Answer

Next

- We will now increase our sample size to 500 samples and change our sampling scheme from SRS to LHS.
- Perform the steps on Slides 7 to 13 for the results in the **S3_500_Epistemic_50_Aleatory_LHS/ S3_Simulation_Results_500E_50A_LHS.xlsx** file.
- Make sure to change your variable names (e.g., **ep100** should now be **ep500**).

How Next

What is the width of your confidence interval after using 500 LHS samples?
How does this compare with the 100 SRS samples?

Answer

Next

SCENARIO 3 CONVERGENCE ANALYSIS 1000 SAMPLES

- We will again increase our sample size. Now we will use 1000 epistemic samples.
- Perform the steps on Slides 7 to 13 for the results in the **S3_1000_Epistemic_50_Aleatory_LHS/ S3_Simulation_Results_1000E_50A_LHS.xlsx** file.
- Make sure to change your variable names (e.g., **ep100** should now be **ep1000**).

How

Next

SCENARIO 3 CONVERGENCE ANALYSIS 1000 SAMPLES

What is the width of your confidence interval after using 1000 LHS samples?
How does this compare with the 500 LHS samples?

Answer

Next

- 1000 LHS samples provides sufficient QoI convergence for our application since the CI width is less than 0.01.
- We will now perform a sensitivity analysis on this converged solution to determine which inputs are contributing to the most uncertainty in the results.

Next

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- Read in the sampled inputs located in **S3_1000_Epistemic_50_Aleatory_LHS/S3_Sensitivity_1000E_50A_LHS.csv** and save it to a variable called **inputs1000**
- Perform a rank regression using the sampled inputs and the epistemic output that is saved as **ep1000**.
- **Hint**: Use the following command after reading in your data to make your regression results easier to read

```
colnames(inputs1000) <- substr(colnames(inputs1000), 1, 5)
```

How Next

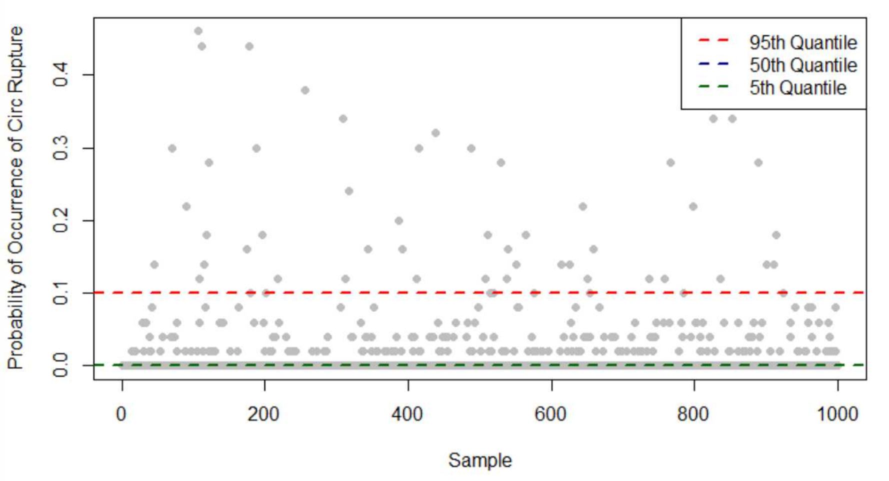
- What is the model R^2 value?
  - What does this tell us?
- What variable is most important?
  - What is its SRRC value?
- What could we do with important variables?

Answer

Next

SCENARIO 3 EPISTEMIC QUANTILES

- Now we will calculate epistemic quantiles.
- Create a scatterplot of **ep1000**. Make sure to add axes labels.
- Calculate the **5th, 50th, and 95th** quantiles for **ep1000**. Plot them as horizontal dashed lines on the scatterplot. Make sure to add a legend. Save your figure.



How

Next

What probability of occurrence of circumferential rupture do 95% of the realizations fall below?

What do these quantiles tell us?

Answer

Next

- Make sure you have filled out all of the information in **Exercises/Scenario_Analysis_Results.xlsx**

Answer

Next

Choose a new scenario:

Scenario 5
MSIP
Mitigation

Scenario 8
Zn & H2
Mitigation

Scenario 9
Inlay
Mitigation

- Scenario 5 MSIP Mitigation
  - Use the data located in **Exercises/Challenge Problems/ Scenario 5**. Set your working directory to this folder.
  - Create a new R script called "Scenario_5.R". Clear your environment variables.

Next

- Scenario 5 MSIP Mitigation
  - Find a converged solution by calculating a bootstrap confidence interval for the mean probability of occurrence of circumferential crack.
    - For this example, we will consider a QoI to be converged if the confidence interval width is less than 0.01.
  - Perform a sensitivity analysis and determine which inputs account for most of the variation in the response.
  - Calculate the 95th, 50th and 5th epistemic quantiles.
  - Save all figures in **Exercises/Challenge Problems/Scenario 5** and record your results in the **Scenario_Analysis_Results.xlsx** file.

Next

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- How do your results compare to Scenario 3?

Answer

Choose Another Scenario

Compare All Scenarios

- Scenario 8 Zn & H2 Mitigation
  - Use the data located in **Exercises/Challenge Problems/ Scenario 8**. Set your working directory to this folder.
  - Create a new R script called "Scenario_8.R". Clear your environment variables.

Next

- Scenario 8 Zn & H2 Mitigation
  - Find a converged solution by calculating a bootstrap confidence interval for the mean probability of occurrence of circumferential crack.
    - For this example, a converged QoI is achieved when the confidence interval width is less than 0.01.
  - Perform a sensitivity analysis and determine which inputs account for most of the variation in the response.
  - Calculate the 95^{th}, 50^{th} and 5^{th} epistemic quantiles.
  - Save all figures in **Exercises/Challenge Problems/Scenario 8** and record your results in the **Scenario_Analysis_Results.xlsx** file.

Next

- How do your results compare to Scenario 3?

Answer

Choose Another Scenario

Compare All Scenarios

- Scenario 9 Inlay Mitigation
  - Use the data located in **Exercises/Challenge Problems/ Scenario 9**. Set your working directory to this folder.
  - Create a new R script called "Scenario_9.R". Clear your environment variables.

Next

- Scenario 9 Inlay Mitigation
  - Find a converged solution by calculating a bootstrap confidence interval for the mean probability of occurrence of circumferential crack.
    - For this example, a converged QoI is achieved when the confidence interval width is less than 0.01.
  - Perform a sensitivity analysis and determine which inputs account for most of the variation in the response.
  - Calculate the 95th, 50th and 5th epistemic quantiles.
  - Save all figures in **Exercises/Challenge Problems/Scenario 9** and record your results in the **Scenario_Analysis_Results.xlsx** file.

Next

- How do your results compare to Scenario 3?

Answer

Choose Another Scenario

Compare All Scenarios

SCENARIO COMPARISONS

Scenario Analysis Results				
	Scenario 3	Scenario 5	Scenario 8	Scenario 9
Description of Scenario	PWSCC No Mitigation	PWSCC MSIP Mitigation	PWSCC Zn & H2 Mitigation	PWSCC Inlay Mitigation
CI Width for 100 Samples	0.0248	0.0176	0.0166	0.0138
CI Width for 500 Samples	0.0096	0.0164	0.0087	0.006
CI Width for 1000 Samples	0.0068	0.0048	0.005	0.0036
Number of Samples in Converged Solution	1000	1000	500	500
Sampling Scheme in Converged Solution	LHS	LHS	SRS	SRS
Sample Mean	0.0183	0.0121	0.0155	0.01056
Bootstrap CI	0.0148, 0.0215	0.00964, 0.01444	0.01072,0.01968	0.0072,0.0134
Sensitivity Analysis Model	Rank Regression	Rank Regression	Rank Regression	Rank Regression
Sensitivity Analysis R2	0.483	0.416	0.457	0.341
Top 3 Important Variables	p2543, p2592, p4352	p2543, p1102, p2592	p2543, p2592, p4352	p2543, p2593, p4352
95th Quantile	0.1	0.08	0.08	0.061
50th Quantile	0	0	0	0
5th Quantile	0	0	0	0

What conclusions can you draw from comparing the scenarios?

Answer

Next

End of Challenge Problem

Answer Key

Sheet 2 contains the results from Occurrence of Circumferential Rupture

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```
library(openxlsx)
# Scenario 3

# 100 ep 50 aleatory SRS
# Read in data
dat <- read.xlsx('S3_100_Epistemic_50_Aleatory_SRS/S3_Simulation_Results_100E_50A_SRS.xlsx',
sheet = 2, startRow = 5)
```

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```
# Get data at year 60
ep100 <- dat[which(dat[,1] == 60),]

# Remove first observation
ep100 <- ep100[-1]

# Change to numeric vector
ep100 <- as.numeric(as.character(ep100))
```

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The mean probability of circumferential rupture for 100 epistemic samples is **0.0278**.

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```r
# Plot histogram of data with vertical line at mean
hist(ep100, col = "lightgrey", xlab = "Probability of Circumferential Rupture")
abline(v = mean(ep100), lty = 2, lwd =2, col = "red")
```

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ANSWER KEY

```r
# Bootstrap confidence interval
# Create bootstrap samples
B <- 1000 # Number of bootstrap samples
mn <- vector()
n <- length(ep100)
for(i in 1:B){
  samp <- sample(ep100, size = n, replace = TRUE)  # Take a sample with replacement
  mn[i] <- mean(samp) # Calculate mean of the bootstrap sample
}
```

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```
# Calcualte "basic" bootstrap confidence interval
alpha <- .05
lb100 <- 2*mean(ep100) - quantile(mn, probs = (1-alpha/2))
ub100 <- 2*mean(ep100) - quantile(mn, probs = alpha/2)

# Plot confidence interval on original data
hist(ep100, col = 'lightgrey', main = "Probability of Occurrence of Circ Rupture")
abline(v = c(lb100, ub100), col = "blue", lty = 2, lwd =2)
abline(v = mean(ep100), col = "red", lty = 2, lwd = 2)
```

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The width of my confidence interval is **.0248**. (This might be slightly different than yours).

This gives an indication of how much **sampling uncertainty** we have in our estimate of the mean probability of occurrence of circumferential rupture.

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```
# Calculate CI width
ciWidth100 <- ub100 - lb100
```

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We can reduce sampling uncertainty by:

1) Increasing our sample size and/or
2) Changing our sampling scheme

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ANSWER KEY

```
# 500 ep 50 aleatory LHS
# Read in data
dat <- read.xlsx('S3_500_Epistemic_50_Aleatory_LHS/S3_Simulation_Results_500E_50A_LHS.xlsx',
sheet = 2, startRow = 5)

# Get data at year 60
ep500 <- dat[which(dat[,1] == 60),]

# Remove first observation
ep500<- ep500[-1]

# Change to numeric vector
ep500 <- as.numeric(as.character(ep500))

# Plot histogram of data with vertical line at mean
hist(ep500, col = "lightgrey", xlab = "Probability of Circumferential Rupture")
abline(v = mean(ep500), lty = 2, lwd =2, col = "red")

# Bootstrap confidence interval
# Create bootstrap samples
B <- 1000 # Number of bootstrap samples
mn <- vector()
n <- length(ep500)
for(i in 1:B){
  samp <- sample(ep500, size = n, replace = TRUE)  # Take a sample with replacement
  mn[i] <- mean(samp) # Calculate mean of the bootstrap sample
}


# Calcualte "basic" bootstrap confidence interval
alpha <- .05
lb500 <- 2*mean(ep500) - quantile(mn, probs = (1-alpha/2))
ub500 <- 2*mean(ep500) - quantile(mn, probs = alpha/2)

# Plot confidence interval on original data
hist(ep500, col = 'lightgrey', main = "Probability of Occurrence of Circ Rupture")
abline(v = c(lb500, ub500), col = "blue", lty = 2, lwd =2)
abline(v = mean(ep500), col = "red", lty = 2, lwd = 2)

# Calculate confidence interval width
ciWidth500 <- ub500 - lb500
```

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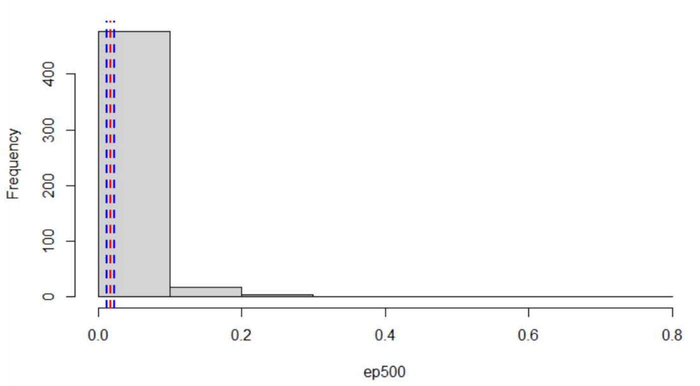
The width of my confidence interval is **.0096**. (Again, this might be slightly different than yours).

This is **smaller** than the width of our CI using 100 epistemic SRS samples. Since we increased our sample size and used LHS, our sampling uncertainty has decreased.



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ANSWER KEY

```
# 1000 ep 50 aleatory LHS
# Read in data
dat <- read.xlsx('S3_1000_Epistemic_50_Aleatory_LHS/S3_Simulation_Results_1000E_50A_LHS.xlsx',
sheet = 2, startRow = 5)

# Get data at year 60
ep1000 <- dat[which(dat[,1] == 60),]

# Remove first observation
ep1000<- ep1000[-1]

# Change to numeric vector
ep1000 <- as.numeric(as.character(ep1000))

# Plot histogram of data with vertical line at mean
hist(ep1000, col = "lightgrey", xlab = "Probability of Circumferential Rupture")
abline(v = mean(ep1000), lty = 2, lwd =2, col = "red")

# Bootstrap confidence interval
# Create bootstrap samples
B <- 1000 # Number of bootstrap samples
mn <- vector()
n <- length(ep1000)
for(i in 1:B){
  samp <- sample(ep1000, size = n, replace = TRUE)  # Take a sample with replacement
  mn[i] <- mean(samp) # Calculate mean of the bootstrap sample
}

# Calcualte "basic" bootstrap confidence interval
alpha <- .05
lb1000 <- 2*mean(ep1000) - quantile(mn, probs = (1-alpha/2))
ub1000 <- 2*mean(ep1000) - quantile(mn, probs = alpha/2)

# Plot confidence interval on original data
hist(ep1000, col = 'lightgrey', main = "Probability of Occurrence of Circ Rupture")
abline(v = c(lb1000, ub1000), col = "blue", lty = 2, lwd =2)
abline(v = mean(ep500), col = "red", lty = 2, lwd = 2)

# Calculate confidence interval width
ciWidth1000 <- ub1000 - lb1000
ciWidth1000
```

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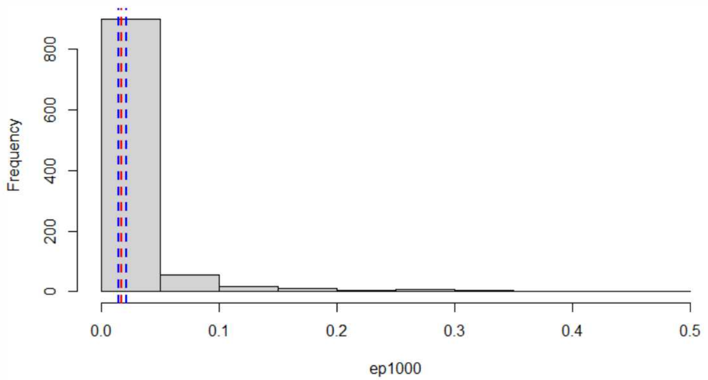
The width of my confidence interval is **.0068**. (Again, this might be slightly different than yours).

This is **smaller** than the width of our CI using 500 epistemic LHS samples. Note that the change in CI width when we went from 100 to 500 samples was larger than when we went from 500 to 1000 samples.



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```
# Perform sensitivity analysis
# Read in sampled input data
library(CompModSA)
inputs1000 <- read.csv("S3_1000_Epistemic_50_Aleatory_LHS/S3_Sensitivity_1000E_50A_LHS.csv",
header = TRUE)
colnames(inputs1000) <- substr(colnames(inputs1000), 1, 5)
# Combine inputs1000 and ep1000 into a data frame

dataCombined <- data.frame(cbind(inputs1000, ep1000))
x.pos <- c(1:42)
y.pos <- 43
rankReg <- CompModSA::sensitivity(dataCombined, x.pos, y.pos, surface = "rank")
print.sensitivity(rankReg)
```

```
####### Output = ep1000 #######

#### surface = rank ####

Estimated Model Summary:
Model: ep1000 = f(p2543, p2592, p4352, p1102, p3102, p2591, p2594, p2595)
Rsq = 0.4827032
dfmod = 9

Input   Rsq     src     pcc^2   95% pcc^2 CI    p-val
p2543   0.372   0.457   0.404   (0.356, 0.450)  0.000
p2592   0.412   0.153   0.071   (0.043, 0.105)  0.000
p4352   0.445   -0.140  0.060   (0.035, 0.092)  0.000
p1102   0.471   -0.126  0.049   (0.026, 0.078)  0.000
p3102   0.474   0.039   0.005   (0.000, 0.017)  0.028
p2591   0.476   0.035   0.004   (0.000, 0.016)  0.048
p2594   0.477   -0.091  0.012   (0.002, 0.030)  0.000
p2595   0.483   0.085   0.011   (0.002, 0.027)  0.001
```

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- What is the model R^2 value? 0.483
  - What does this tell us? It tells us what percentage of the variance in the output rank regression is able to account for.
- What variable is most important? p2543 Multiplier proportional constant
  - What is its SRRC value? 0.457
- What could we do with important variables? We could use them for importance sampling, or try to reduce the amount of uncertainty for those inputs.

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```
# Perform epistemic uncertainty analysis
epQuantile <- quantile(ep1000, probs = c(0.95, 0.50, 0.05))

plot(ep1000, pch = 16, xlab = "Sample", col = "grey", ylab = "Probability of Occurrence of Circ
Rupture")

abline(h=epQuantile, col = c("red", "darkblue", "darkgreen"), lty = 2, lwd =2 )

legend('topright', legend = c('95th Quantile', '50th Quantile', '5th Quantile'),
       col =c("red", "darkblue", "darkgreen"), lty = c(2,2,2), lwd = c(2,2,2))
```

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- 95% of the realizations fall below **0.1** probability of occurrence of circumferential rupture.
- These quantiles give us an estimation of **uncertainty due to lack of knowledge**.

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- Scenario 3 Results

	Scenario 3
Description of Scenario	PWSCC No Mitigation
CI Width for 100 SRS	0.0248
CI Width for 500 LHS	0.0096
CI Width for 1000 LHS	0.0068
Number of Samples in Converged Solution	1000
Sampling Scheme in Converged Solution	LHS
Sample Mean	0.0183
Bootstrap CI	0.0148, 0.0215
Sensitivity Analysis Model	Rank Regression
Sensitivity Analysis R2	0.483
Top 3 Important Variables	p2543, p2592, p4352
95th Quantile	0.1
50th Quantile	0
5th Quantile	0

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• Scenario 5 Results

	Scenario 3	Scenario 5
Description of Scenario	PWSCC No Mitigation	PWSCC MSIP Mitigation
CI Width for 100 SRS	0.0248	0.0176
CI Width for 500 LHS	0.0096	0.0172
CI Width for 1000 LHS	0.0068	0.0048
Number of Samples in Converged Solution	1000	1000
Sampling Scheme in Converged Solution	LHS	LHS
Sample Mean	0.0183	0.0121
Bootstrap CI	0.0148, 0.0215	0.00964, 0.01444
Sensitivity Analysis Model	Rank Regression	Rank Regression
Sensitivity Analysis R2	0.483	0.416
Top 3 Important Variables	p2543, p2592, p4352	p2543, p1102, p2592
95th Quantile	0.1	0.08
50th Quantile	0	0
5th Quantile	0	0

Scenario 5 has a lower mean probability of occurrence of circumferential rupture.

p2543 is the most important variable in both cases.

The 95^{th} quantile for scenario 5 is .02 lower than scenario 3.

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- Scenario 8 Results

	Scenario 3	Scenario 8
Description of Scenario	PWSCC No Mitigation	PWSCC Zn & H2 Mitigation
CI Width for 100 SRS	0.0248	0.0166
CI Width for 500 LHS	0.0096	0.0087
CI Width for 1000 LHS	0.0068	0.005
Number of Samples in Converged Solution	1000	500
Sampling Scheme in Converged Solution	LHS	SRS
Sample Mean	0.0183	0.0155
Bootstrap CI	0.0148, 0.0215	0.01072,0.01968
Sensitivity Analysis Model	Rank Regression	Rank Regression
Sensitivity Analysis R2	0.483	0.457
Top 3 Important Variables	p2543, p2592, p4352	p2543, p2592, p4352
95th Quantile	0.1	0.08
50th Quantile	0	0
5th Quantile	0	0

Scenario 8 has a slightly lower mean probability of occurrence of circumferential rupture.

Both scenarios have the same top 3 important variables.

The 95th quantile for scenario 8 is .02 lower than scenario 3.

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- # Scenario 9 Results

	Scenario 3	Scenario 9
Description of Scenario	PWSCC No Mitigation	PWSCC Inlay Mitigation
CI Width for 100 SRS	0.0248	0.0138
CI Width for 500 LHS	0.0096	0.006
CI Width for 1000 LHS	0.0068	0.0036
Number of Samples in Converged Solution	1000	500
Sampling Scheme in Converged Solution	LHS	SRS
Sample Mean	0.0183	0.01056
Bootstrap CI	0.0148, 0.0215	0.0072,0.0134
Sensitivity Analysis Model	Rank Regression	Rank Regression
Sensitivity Analysis R2	0.483	0.341
Top 3 Important Variables	p2543, p2592, p4352	p2543, p2593, p4352
95th Quantile	0.1	0.061
50th Quantile	0	0
5th Quantile	0	0

Scenario 9 has a lower mean probability of occurrence of circumferential rupture.

p2543 is the most important variable in both cases.

The 95th quantile for scenario 5 is ~.04 lower than scenario 3.

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ANSWER KEY

Scenario Analysis Results				
	Scenario 3	Scenario 5	Scenario 8	Scenario 9
Description of Scenario	PWSCC No Mitigation	PWSCC MSIP Mitigation	PWSCC Zn & H2 Mitigation	PWSCC Inlay Mitigation
CI Width for 100 Samples	0.0248	0.0176	0.0166	0.0138
CI Width for 500 Samples	0.0096	0.0164	0.0087	0.006
CI Width for 1000 Samples	0.0068	0.0048	0.005	0.0036
Number of Samples in Converged Solution	1000	1000	500	500
Sampling Scheme in Converged Solution	LHS	LHS	SRS	SRS
Sample Mean	0.0183	0.0121	0.0155	0.01056
Bootstrap CI	0.0148, 0.0215	0.00964, 0.01444	0.01072,0.01968	0.0072,0.0134
Sensitivity Analysis Model	Rank Regression	Rank Regression	Rank Regression	Rank Regression
Sensitivity Analysis R2	0.483	0.416	0.457	0.341
Top 3 Important Variables	p2543, p2592, p4352	p2543, p1102, p2592	p2543, p2592, p4352	p2543, p2593, p4352
95th Quantile	0.1	0.08	0.08	0.061
50th Quantile	0	0	0	0
5th Quantile	0	0	0	0

- **Inlay mitigation** results in the **lowest mean probability** of occurrence of circumferential rupture, as well as the **smallest amount of uncertainty due to lack of knowledge**.
- **p2543** is the most **significant variable** in all scenarios.
- All methods of mitigation result in a decrease in the mean probability of circumferential rupture.

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