Homework 6 - Week 6

Question 14.1

The breast cancer data set breast-cancer-wisconsin.data.txt from [http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/ (http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/)](http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/) (description at [http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Original%29 (http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Original%29)](http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Original%29)) has missing values.

1. Use the mean/mode imputation method to impute values for the missing data.
2. Use regression to impute values for the missing data.
3. Use regression with perturbation to impute values for the missing data.
4. (Optional) Compare the results and quality of classification models (e.g., SVM, KNN) build using
   A. the data sets from questions 1,2,3;
   B. the data that remains after data points with missing values are removed; and
   C. the data set when a binary variable is introduced to indicate missing values.

First I have used mean impuation method, then mode imputation, then using regression to impute missing data, and lastly with perturbation to impute the missing data. I have tried to check the accuracy of the imputed data by checking the model accuracy of a regression model created using the imputed data.

In [1]:
```
cancer_data <- read.table("breast-cancer-wisconsin.data.txt", sep = ",",na = c('?'))
head(cancer_data)
```

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
1000025	5	1	1	1	2	1	3	1	1	2
1002945	5	4	4	5	7	10	3	2	1	2
1015425	3	1	1	1	2	2	3	1	1	2
1016277	6	8	8	1	3	4	3	7	1	2
1017023	4	1	1	3	2	1	3	1	1	2
1017122	8	10	10	8	7	10	9	7	1	4

In [2]:
```
cancer_data$V11[which(cancer_data$V11 == 2)] = "Benign"
cancer_data$V11[which(cancer_data$V11 == 4)] = "Malignant"
```

In [3]:
```
summary(cancer_data)
```

```
       V1                  V2               V3               V4        
 Min.   :   61634   Min.   : 1.000   Min.   : 1.000   Min.   : 1.000  
 1st Qu.:  870688   1st Qu.: 2.000   1st Qu.: 1.000   1st Qu.: 1.000  
 Median : 1171710   Median : 4.000   Median : 1.000   Median : 1.000  
 Mean   : 1071704   Mean   : 4.418   Mean   : 3.134   Mean   : 3.207  
 3rd Qu.: 1238298   3rd Qu.: 6.000   3rd Qu.: 5.000   3rd Qu.: 5.000  
 Max.   :13454352   Max.   :10.000   Max.   :10.000   Max.   :10.000  
                                                                      
       V5               V6               V7               V8        
 Min.   : 1.000   Min.   : 1.000   Min.   : 1.000   Min.   : 1.000  
 1st Qu.: 1.000   1st Qu.: 2.000   1st Qu.: 1.000   1st Qu.: 2.000  
 Median : 1.000   Median : 2.000   Median : 1.000   Median : 3.000  
 Mean   : 2.807   Mean   : 3.216   Mean   : 3.545   Mean   : 3.438  
 3rd Qu.: 4.000   3rd Qu.: 4.000   3rd Qu.: 6.000   3rd Qu.: 5.000  
 Max.   :10.000   Max.   :10.000   Max.   :10.000   Max.   :10.000  
                                   NA's   :16                       
       V9              V10              V11           
 Min.   : 1.000   Min.   : 1.000   Length:699        
 1st Qu.: 1.000   1st Qu.: 1.000   Class :character  
 Median : 1.000   Median : 1.000   Mode  :character  
 Mean   : 2.867   Mean   : 1.589                     
 3rd Qu.: 4.000   3rd Qu.: 1.000                     
 Max.   :10.000   Max.   :10.000                     
```

Apparently V7 has 16 missing values. Next, Lets calculate percent of missing data

In [4]:
```
percent_miss <- function(x){sum(is.na(x))/length(x)*100}
apply(cancer_data, 2, percent_miss)
```

V1	0
V2	0
V3	0
V4	0
V5	0
V6	0
V7	2.28898426323319
V8	0
V9	0
V10	0
V11	0

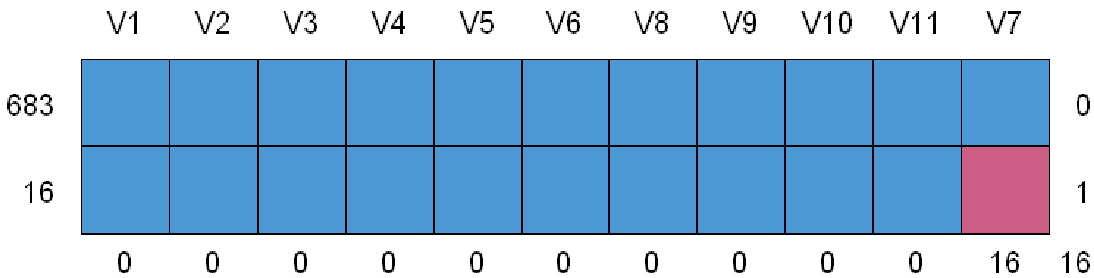
So thats about 2.29% of data that is missing

Using library(mice) for looking at missing data pattern.

In [6]:
```
library(mice)
```

In [7]:
```
md.pattern(cancer_data)
```

	V1	V2	V3	V4	V5	V6	V8	V9	V10	V11	V7	
683	1	1	1	1	1	1	1	1	1	1	1	0
16	1	1	1	1	1	1	1	1	1	1	0	1
	0	0	0	0	0	0	0	0	0	0	16	16

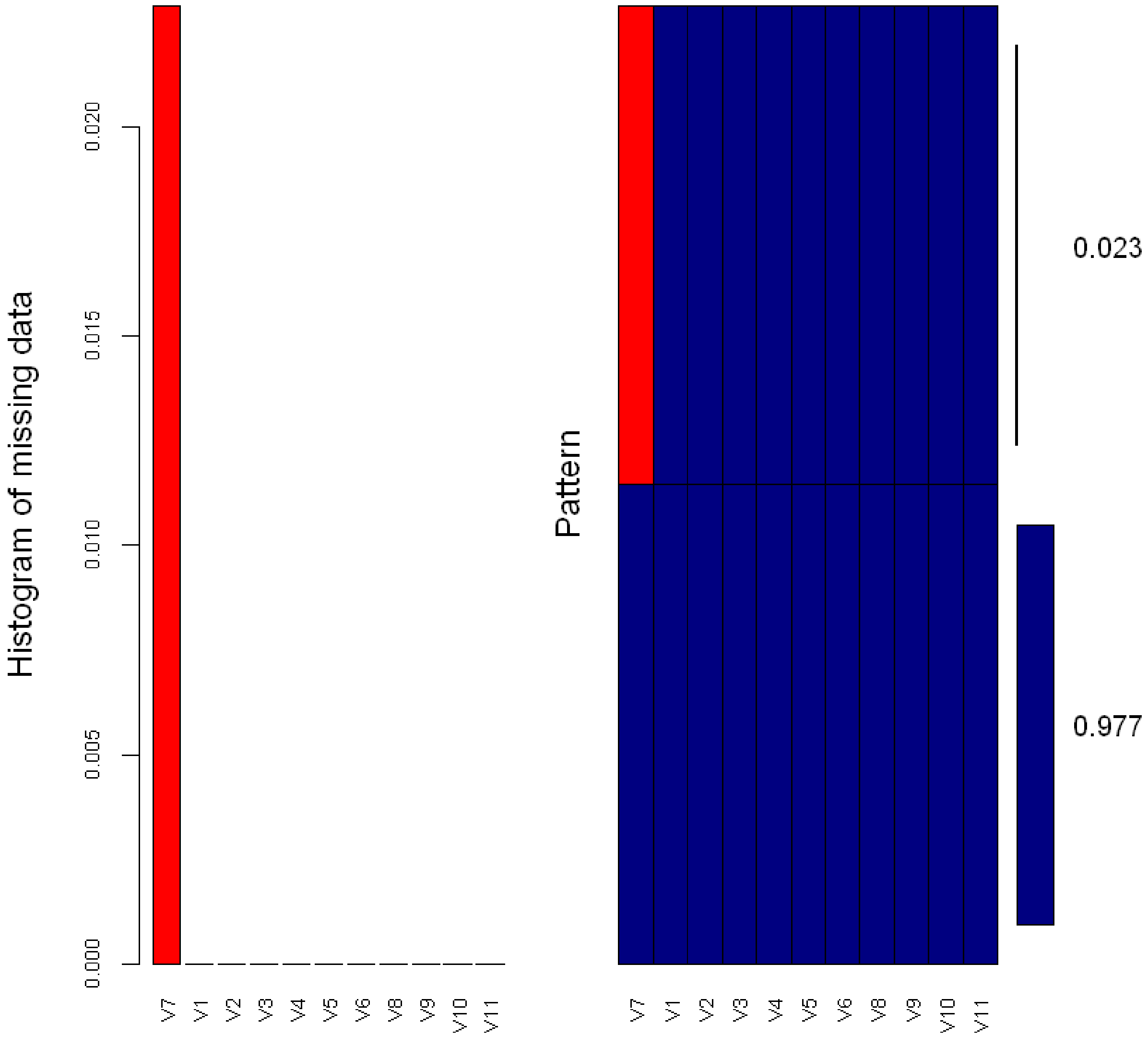


The output tells us that 683 samples are complete, 16 samples miss only in V7 (Bare Nuclei). Next, I am going to visualize this using the VIM package

In [9]:
```
# install.packages("VIM", repos='http://cran.us.r-project.org')
library(VIM)
```

In [10]:
```
aggr_plot <- aggr(cancer_data, col=c('navyblue','red'), numbers=TRUE, sortVars=TRUE,
                  labels=names(cancer_data), cex.axis=.7, gap=3,
                  ylab=c("Histogram of missing data","Pattern")
                 )
```

```
Variables sorted by number of missings:
Variable      Count
      V7 0.02288984
      V1 0.00000000
      V2 0.00000000
      V3 0.00000000
      V4 0.00000000
      V5 0.00000000
      V6 0.00000000
      V8 0.00000000
      V9 0.00000000
     V10 0.00000000
     V11 0.00000000
```



The above histogram shows that almost 97.7% of dataset is not missing any data. 2.29% of missing values seem to be concentrated in V7.

Now, I am going to use mean imputation technique

In [11]:
```
cancer_data_mean <- cancer_data
```

In [12]:
```
head(cancer_data_mean)
```

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
1000025	5	1	1	1	2	1	3	1	1	Benign
1002945	5	4	4	5	7	10	3	2	1	Benign
1015425	3	1	1	1	2	2	3	1	1	Benign
1016277	6	8	8	1	3	4	3	7	1	Benign
1017023	4	1	1	3	2	1	3	1	1	Benign
1017122	8	10	10	8	7	10	9	7	1	Malignant

The below is a way of showing missing data in a dataset. This shows that column V7 has 16 missing values.

In [13]:
```
sapply(cancer_data_mean, function(x) sum(is.na(x)))
```

V1	0
V2	0
V3	0
V4	0
V5	0
V6	0
V7	16
V8	0
V9	0
V10	0
V11	0

In [14]:
```
for(i in 1:ncol(cancer_data_mean[,-11])){
    cancer_data_mean[is.na(cancer_data_mean[,i]), i] <- round(mean(cancer_data_mean[,i], na.rm = TRUE
}
```

In [15]:
```
# Checking if any missing values in the imputed data set. Shows no missing values
sapply(cancer_data_mean, function(x) sum(is.na(x)))
```

V1	0
V2	0
V3	0
V4	0
V5	0
V6	0
V7	0
V8	0
V9	0
V10	0
V11	0

Next, I am going to use mode imputation technique. I got the Mode function from stackoverflow link:

https://stackoverflow.com/questions/2547402/is-there-a-built-in-function-for-finding-the-mode/8189441#8189441 (https://stackoverflow.com/questions/2547402/is-there-a-built-in-function-for-finding-the-mode/8189441#8189441)

In [16]:
```
sapply(cancer_data, function(x) sum(is.na(x)))
```

V1	0
V2	0
V3	0
V4	0
V5	0
V6	0
V7	16
V8	0
V9	0
V10	0
V11	0

In [17]:
```
cancer_data_mode <- cancer_data
```

In [18]:
```
val <- unique(cancer_data_mode[!is.na(cancer_data_mode)])
```

In [19]:
```
val <- unique(cancer_data_mode[!is.na(cancer_data_mode)]) # Values in cancer_data_mode
mode <- val[which.max(tabulate(match(cancer_data_mode, val)))] # Mode of cancer_data_mode
```

In [20]:
```
mode
```

' 1000025'

In [21]:
```
cancer_data_imp <- cancer_data_mode # Replicate vec_miss
cancer_data_imp[is.na(cancer_data_imp)] <- mode # Impute by mode
```

In [22]:
```
indices <- which(!is.na(cancer_data_mode$V7), arr.ind = T)
```

In [23]:
```
Mode <- function(x) {
    ux <- unique(x)
    ux[which.max(tabulate(match(x, ux)))]
}

mode_value <- Mode(cancer_data_mode$V7[indices])
cancer_data_mode$V7[-indices] <- mode_value
```

In [24]:
```
sapply(cancer_data_mode, function(x) sum(is.na(x)))
```

V1	0
V2	0
V3	0
V4	0
V5	0
V6	0
V7	0
V8	0
V9	0
V10	0
V11	0

Using regression (using mice) to impute missing data

In [25]:
```
mice_data <- cancer_data
mice_data$V11[which(mice_data$V11 == 'Benign')] = 2
mice_data$V11[which(mice_data$V11 == 'Malignant')] = 4
head(mice_data)
```

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
1000025	5	1	1	1	2	1	3	1	1	2
1002945	5	4	4	5	7	10	3	2	1	2
1015425	3	1	1	1	2	2	3	1	1	2
1016277	6	8	8	1	3	4	3	7	1	2
1017023	4	1	1	3	2	1	3	1	1	2
1017122	8	10	10	8	7	10	9	7	1	4

From mice documentation,

meth = 'norm.predict' is Imputation by linear regression through prediction

meth = 'norm.nob' is Imputation by linear regression without parameter uncertainty (with perturbation)

In [26]:
```
# Imputation by linear regression through prediction

imp.mice <- mice(mice_data, m=1, maxit=50, meth='norm.predict', seed=500)
# summary(imp.mice)
```

```
 iter imp variable
  1   1  V7
  2   1  V7
  3   1  V7
  4   1  V7
  5   1  V7
  6   1  V7
  7   1  V7
  8   1  V7
  9   1  V7
  10   1  V7
  11   1  V7
  12   1  V7
  13   1  V7
  14   1  V7
  15   1  V7
  16   1  V7
  17   1  V7
  18   1  V7
  19   1  V7
  20   1  V7
  21   1  V7
  22   1  V7
  23   1  V7
  24   1  V7
  25   1  V7
  26   1  V7
  27   1  V7
  28   1  V7
  29   1  V7
  30   1  V7
  31   1  V7
  32   1  V7
  33   1  V7
  34   1  V7
  35   1  V7
  36   1  V7
  37   1  V7
  38   1  V7
  39   1  V7
  40   1  V7
  41   1  V7
  42   1  V7
  43   1  V7
  44   1  V7
  45   1  V7
  46   1  V7
  47   1  V7
  48   1  V7
  49   1  V7
  50   1  V7

Warning message:
"Number of logged events: 1"
```

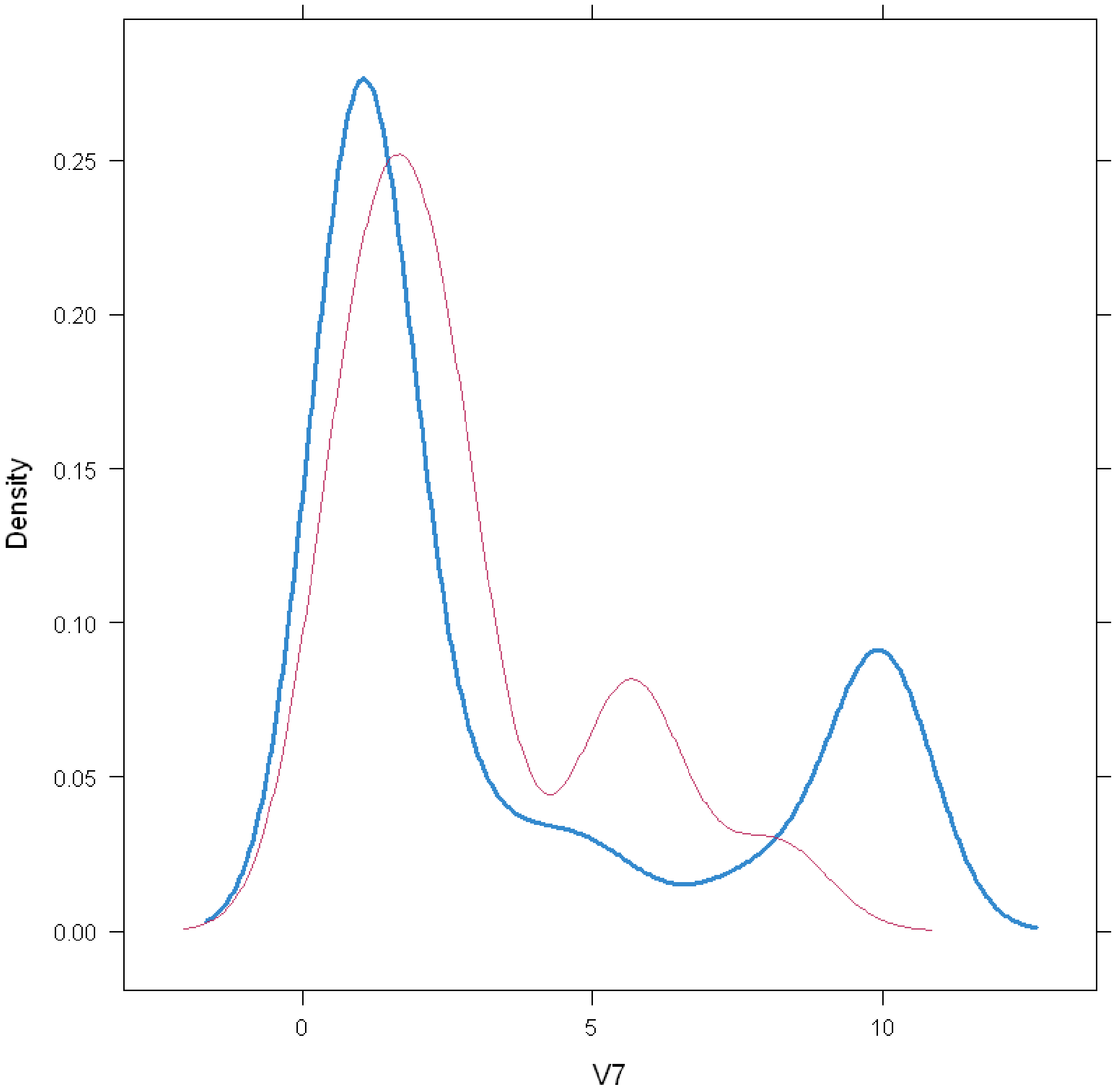
In [27]:
```
imp.mice$imp$V7
```

	1
24	5.3669508
41	8.1907122
140	0.8738591
146	1.6463893
159	1.0731978
165	2.1870186
236	2.7459168
250	2.0127161
276	2.3072038
293	5.9989744
295	1.1204527
298	2.6839366
316	5.6353059
322	1.8585015
412	0.8587684
618	0.5907393

The output shows the imputed data for each observation (first column left) within each imputed dataset (first row at the top). Next, using the complete() function, I am getting a completed dataset. Here, the missing values have been replaced with the imputed values in the first of the five datasets.

Inspecting the distribution of original and imputed data : The density of the imputed data for each imputed dataset is showed in magenta while the density of the observed data is showed in blue.

In [28]:
```
densityplot(imp.mice)
```



In [29]:
```
completed_cancer_data <- complete(imp.mice,1)
```

In [30]:
```
lm.mice.out <- with(imp.mice, lm(V11 ~ V1+V2+V3+V4+V5+V6+V7+V8+V9+V10))
pool.mice <- pool(lm.mice.out)
summary(pool.mice)
```

```
Warning message in pool(lm.mice.out):
"Number of multiple imputations m = 1. No pooling done."


Call:
lm(formula = V11 ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 +
    V10)

Residuals:
     Min       1Q   Median       3Q      Max
-1.86894 -0.16715 -0.01559  0.12651  1.53436

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.519e+00  4.299e-02  35.339  < 2e-16 ***
V1          -1.450e-08  2.401e-08  -0.604 0.546091
V2           6.466e-02  7.240e-03   8.932  < 2e-16 ***
V3           4.489e-02  1.294e-02   3.469 0.000556 ***
V4           3.375e-02  1.264e-02   2.670 0.007775 **
V5           1.230e-02  8.089e-03   1.520 0.128891
V6           1.551e-02  1.061e-02   1.463 0.144013
V7           9.040e-02  6.606e-03  13.684  < 2e-16 ***
V8           4.124e-02  1.024e-02   4.026 6.31e-05 ***
V9           3.327e-02  7.533e-03   4.417 1.16e-05 ***
V10          6.756e-03  1.012e-02   0.667 0.504680
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.389 on 688 degrees of freedom
Multiple R-squared:  0.8352,	Adjusted R-squared:  0.8328
F-statistic: 348.7 on 10 and 688 DF,  p-value: < 2.2e-16
```

Without perturbation, the fitted regression model with the imputed values seem to have a p-value of <<< 0.001 . and R2 value of 83%

Next, Imputation by linear regression without parameter uncertainty (with perturbation)

In [31]:
```
imp.mice.pert <- mice(mice_data, m=1, maxit=50, meth='norm.nob', seed=500)
summary(imp.mice.pert)
```

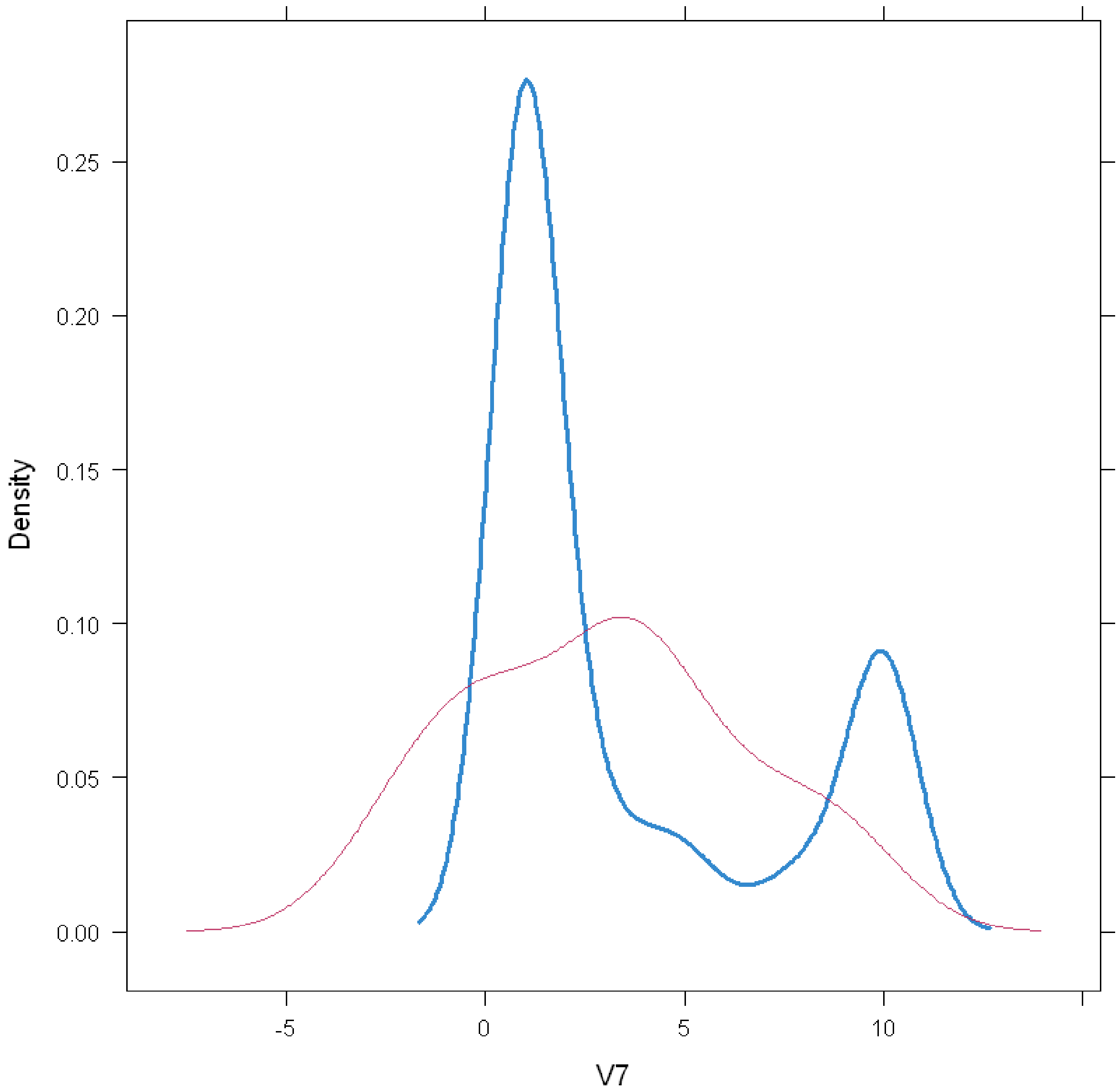
```
 iter imp variable
  1   1  V7
  2   1  V7
  3   1  V7
  4   1  V7
  5   1  V7
  6   1  V7
  7   1  V7
  8   1  V7
  9   1  V7
  10   1  V7
  11   1  V7
  12   1  V7
  13   1  V7
  14   1  V7
  15   1  V7
  16   1  V7
  17   1  V7
  18   1  V7
  19   1  V7
  20   1  V7
  21   1  V7
  22   1  V7
  23   1  V7
  24   1  V7
  25   1  V7
  26   1  V7
  27   1  V7
  28   1  V7
  29   1  V7
  30   1  V7
  31   1  V7
  32   1  V7
  33   1  V7
  34   1  V7
  35   1  V7
  36   1  V7
  37   1  V7
  38   1  V7
  39   1  V7
  40   1  V7
  41   1  V7
  42   1  V7
  43   1  V7
  44   1  V7
  45   1  V7
  46   1  V7
  47   1  V7
  48   1  V7
  49   1  V7
  50   1  V7

Warning message:
"Number of logged events: 1"

Class: mids
Number of multiple imputations:  1
Imputation methods:
        V1         V2         V3         V4         V5         V6         V7
        ""         ""         ""         ""         ""         "" "norm.nob"
        V8         V9        V10        V11
        ""         ""         ""         ""
PredictorMatrix:
   V1 V2 V3 V4 V5 V6 V7 V8 V9 V10 V11
V1  0  1  1  1  1  1  1  1  1   1   0
V2  1  0  1  1  1  1  1  1  1   1   0
V3  1  1  0  1  1  1  1  1  1   1   0
V4  1  1  1  0  1  1  1  1  1   1   0
V5  1  1  1  1  0  1  1  1  1   1   0
V6  1  1  1  1  1  0  1  1  1   1   0
Number of logged events:  1
```

```
  it im dep      meth out
1  0  0      constant V11
```

In [32]:
```
imp.pert.vals <- round(imp.mice.pert$imp$V7)
```

Inspecting the distribution of original and imputed data using density plot. After that, using the complete() function, I am getting a completed dataset. Here, the missing values have been replaced with the imputed values in the first of the five datasets

In [33]:
```
densityplot(imp.mice.pert)
```



In [34]:
```
completed_pert_cancer_data <- complete(imp.mice.pert)
```

Checking the data quality by creating a regression model using the imputed data and checking the model quality

In [35]:
```
lm.mice.out_pert <- with(imp.mice.pert, lm(V11 ~ V1+V2+V3+V4+V5+V6+V7+V8+V9+V10))
pool.mice_pert <- pool(lm.mice.out_pert)
summary(pool.mice_pert)
```

```
Warning message in pool(lm.mice.out_pert):
"Number of multiple imputations m = 1. No pooling done."


Call:
lm(formula = V11 ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 + 
    V10)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.91760 -0.16819 -0.01681  0.11971  1.54040 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.517e+00  4.319e-02  35.135  < 2e-16 ***
V1          -1.392e-08  2.412e-08  -0.577 0.564068    
V2           6.487e-02  7.276e-03   8.916  < 2e-16 ***
V3           4.399e-02  1.300e-02   3.384 0.000755 ***
V4           3.487e-02  1.270e-02   2.747 0.006175 ** 
V5           1.351e-02  8.114e-03   1.665 0.096436 .  
V6           1.640e-02  1.065e-02   1.540 0.124072    
V7           8.807e-02  6.582e-03  13.381  < 2e-16 ***
V8           4.202e-02  1.029e-02   4.084 4.95e-05 ***
V9           3.258e-02  7.569e-03   4.305 1.92e-05 ***
V10          7.010e-03  1.017e-02   0.689 0.490906    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3908 on 688 degrees of freedom
Multiple R-squared:  0.8336,	Adjusted R-squared:  0.8312 
F-statistic: 344.7 on 10 and 688 DF,  p-value: < 2.2e-16
```

Here, the fitted regression model with the imputed values seem to have a p-value of < 0.001 . and R2 value of 83%

In [ ]:

Question 15.1

Describe a situation or problem from your job, everyday life, current events, etc., for which optimization would be appropriate. What data would you need?

One place I can think of where optimization will be a great fit is a warehouse unit. Example, Amazon's or Walmart's warehouses where the number of items stored to be retrieved (each can be its own data point). Optimization to figure out a warehouse layout and placing the items strategically to minimize time needed to stock and retrieve with minimal error, comes to my mind as a good optimization problem. Self driving cars, autonomous vehicles trying to solve transportation for the future itself is a huge optimization problem.

Or strategizing layout of roads and transportation in a new township is also a good problem. For the township problem, the data needed would be maximum number of residents that can stay at a given time in the township, maximum number of vehicles estimated on road, identifying whether the township will have a school district or hospitals (so as to device alternate routes), and the end goal is to minimize the time for travel while also minimizing the predicted number of accidents (fatalities included) in the township.

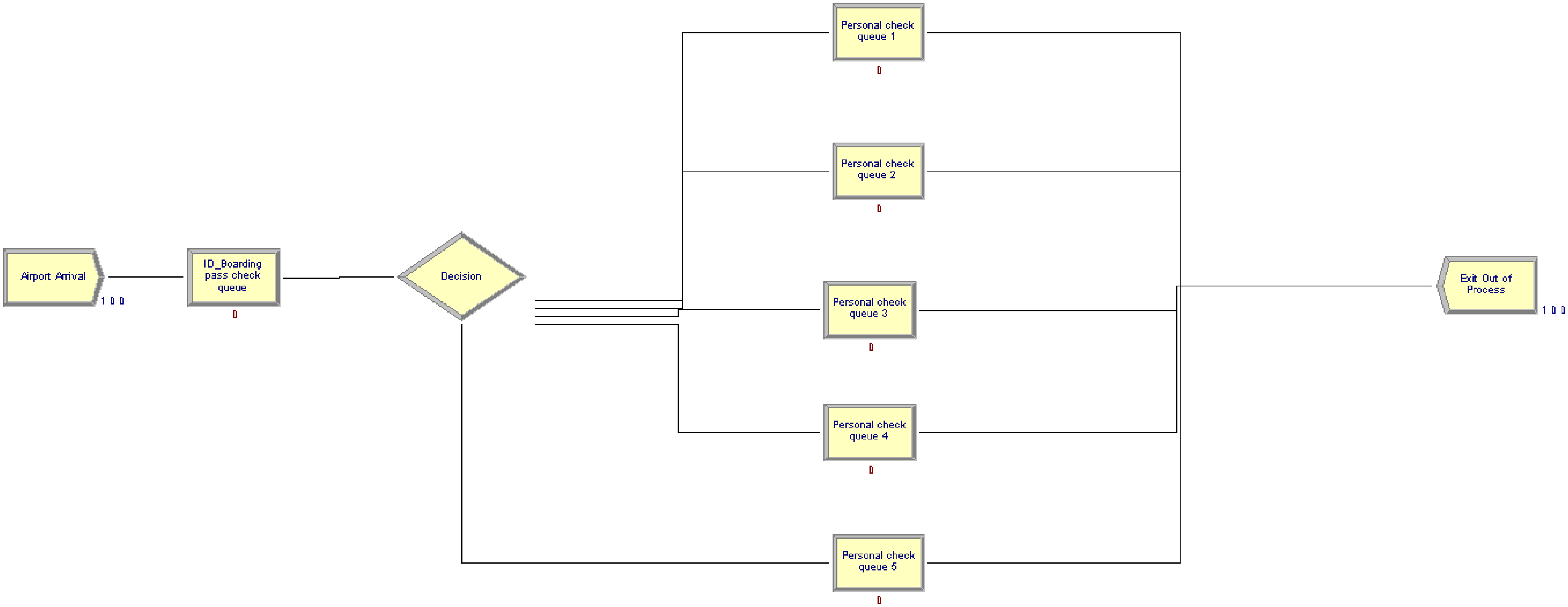
In [ ]:

In [ ]:

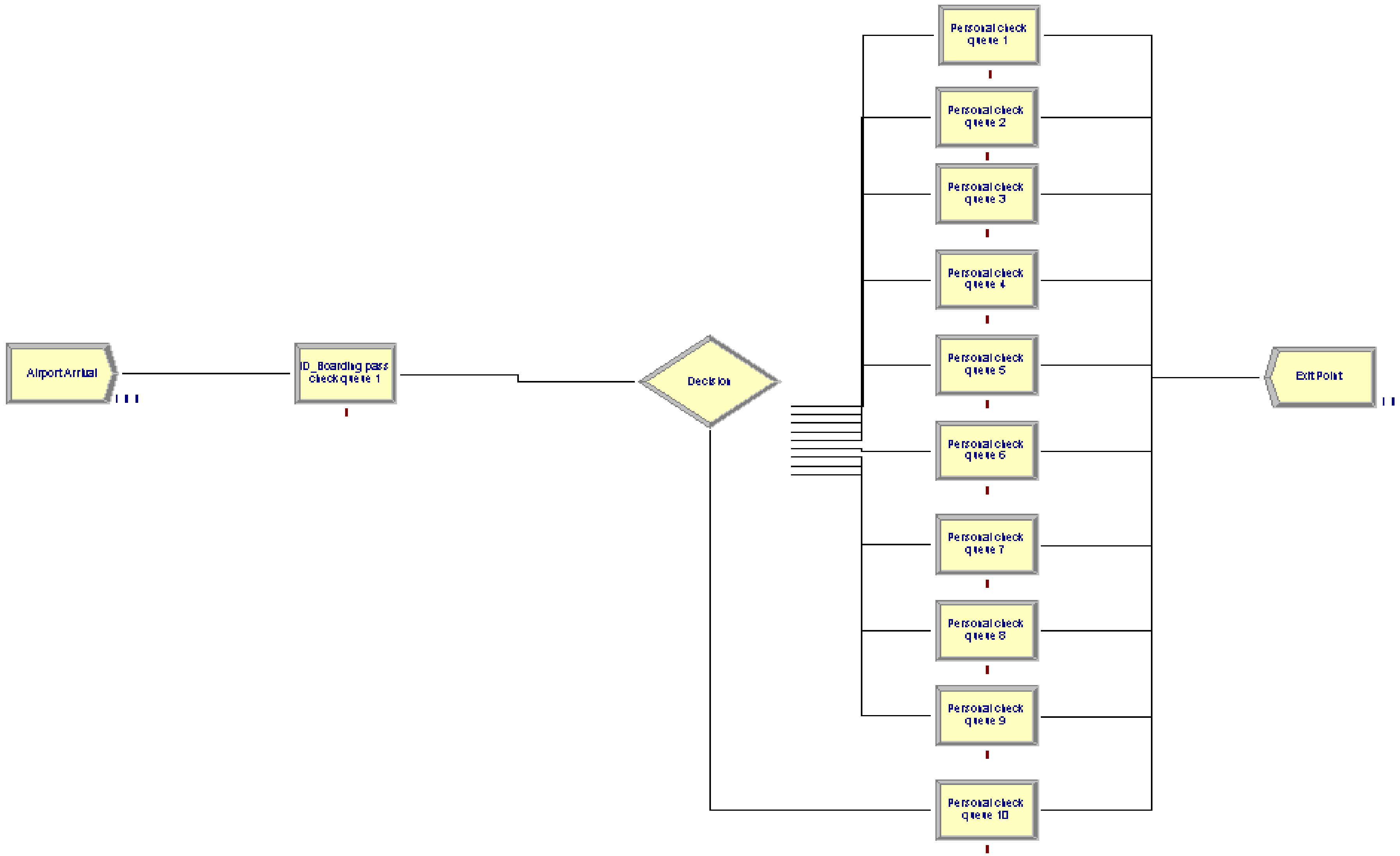
Question 13.2

This model has five personal check queues with 2 resources in each queue except for queue 3 which has 3 resources. The ID Check queue has 3 resources.

Plugging in the distributions as mentioned in the problem for each step, the estimated total time for 100 observations, averaged over a 24-hour period is found to be 32.5468 minutes. I have created another model which I have discussed about in the next parts of this report.



In this part, I am using 10 check queues with 3 scanners for queue 1 – 9 and 4 for queue 10. The ID Boarding pass check queue has 4 scanners. Plugging in the distributions as mentioned in the problem for each step, the estimated total time for 100 observations, averaged over a 24-hour period is found to be 32.5468 minutes. Perhaps, increasing the number of scanners and queues will decrease the total wait time further. I have attached the report for the second model as a part of the assignment.



Airport Arrival
ID_Boarding pass check queue 1
Decision
Personal check queue 1
Personal check queue 2
Personal check queue 3
Personal check queue 4
Personal check queue 5
Personal check queue 6
Personal check queue 7
Personal check queue 8
Personal check queue 9
Personal check queue 10
Exit Point

Airport Simulation

Replications: 100 Time Units: Minutes

Key Performance Indicators

System	Average
Number Out	100

Airport Simulation

Replications: 100 Time Units: Minutes

Entity

Time

VA Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	1.5136	0.02	1.3491	1.7246	0.5041	7.4418

NVA Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Wait Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	31.0332	0.73	24.4078	44.5499	0.00	79.3982

Transfer Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Other Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Total Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	32.5468	0.74	25.7569	46.1973	0.5625	80.8856

Other

Number In	Average	Half Width	Minimum Average	Maximum Average
Entity 1	100.00	0.00	100.00	100.00

Number Out	Average	Half Width	Minimum Average	Maximum Average
Entity 1	100.00	0.00	100.00	100.00

WIP	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	2.2602	0.05	1.7887	3.2081	0.00	90.0000

Airport Simulation

Replications: 100 Time Units: Minutes

Queue

Time

Waiting Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
ID_Boarding pass check queue 1.Queue	27.7210	0.94	17.3094	42.2361	0.00	78.8882
Personal check queue 1.Queue	1.9350	0.31	0.3912	9.3989	0.00	20.2424
Personal check queue 10.Queue	4.2477	0.84	0.00	13.0123	0.00	18.5263
Personal check queue 2.Queue	3.0893	0.34	1.2078	11.1208	0.5167	20.3053
Personal check queue 3.Queue	3.6868	0.34	1.6587	10.1587	1.1184	17.8567
Personal check queue 4.Queue	4.3175	0.36	2.3646	11.8136	1.7279	18.9379
Personal check queue 5.Queue	4.6569	0.37	0.00	12.0759	0.00	18.6690
Personal check queue 6.Queue	5.1067	0.38	0.00	11.4673	0.00	19.1110
Personal check queue 7.Queue	5.3652	0.48	0.00	12.6660	0.00	20.0345
Personal check queue 8.Queue	5.4226	0.58	0.00	13.3837	0.00	20.2732
Personal check queue 9.Queue	5.1364	0.71	0.00	13.9367	0.00	21.0518

Other

Number Waiting	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
ID_Boarding pass check queue 1.Queue	1.9251	0.07	1.2020	2.9331	0.00	89.0000
Personal check queue 1.Queue	0.04087914	0.00	0.01983382	0.0983	0.00	3.0000
Personal check queue 10.Queue	0.00878014	0.00	0.00	0.05421810	0.00	2.0000
Personal check queue 2.Queue	0.03700759	0.00	0.01519656	0.1081	0.00	3.0000
Personal check queue 3.Queue	0.03109814	0.00	0.00693309	0.07760152	0.00	3.0000
Personal check queue 4.Queue	0.02713391	0.00	0.00338652	0.0902	0.00	3.0000
Personal check queue 5.Queue	0.02300656	0.00	0.00	0.08386065	0.00	3.0000
Personal check queue 6.Queue	0.01952798	0.00	0.00	0.07167091	0.00	3.0000
Personal check queue 7.Queue	0.01661946	0.00	0.00	0.07916280	0.00	3.0000
Personal check queue 8.Queue	0.01430663	0.00	0.00	0.07435372	0.00	3.0000
Personal check queue 9.Queue	0.01165734	0.00	0.00	0.06774763	0.00	3.0000

Airport Simulation

Replications: 100 Time Units: Minutes

Resource

Usage

Instantaneous Utilization	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Scanner 1	0.05205132	0.00	0.04984521	0.05393922	0.00	1.0000
Scanner 2	0.05205132	0.00	0.04984521	0.05393922	0.00	1.0000
Scanner 3	0.05205132	0.00	0.04984521	0.05393922	0.00	1.0000
Scanner 4	0.00076118	0.00	0.00	0.00313006	0.00	1.0000
Server 1	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000
Server 2	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000
Server 3	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000
Server 4	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000

Number Busy	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Scanner 1	0.05205132	0.00	0.04984521	0.05393922	0.00	1.0000
Scanner 2	0.05205132	0.00	0.04984521	0.05393922	0.00	1.0000
Scanner 3	0.05205132	0.00	0.04984521	0.05393922	0.00	1.0000
Scanner 4	0.00076118	0.00	0.00	0.00313006	0.00	1.0000
Server 1	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000
Server 2	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000
Server 3	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000
Server 4	0.05305837	0.00	0.04253213	0.06834889	0.00	1.0000

Number Scheduled	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Scanner 1	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Scanner 2	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Scanner 3	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Scanner 4	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Server 1	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Server 2	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Server 3	1.0000	0.00	1.0000	1.0000	1.0000	1.0000
Server 4	1.0000	0.00	1.0000	1.0000	1.0000	1.0000

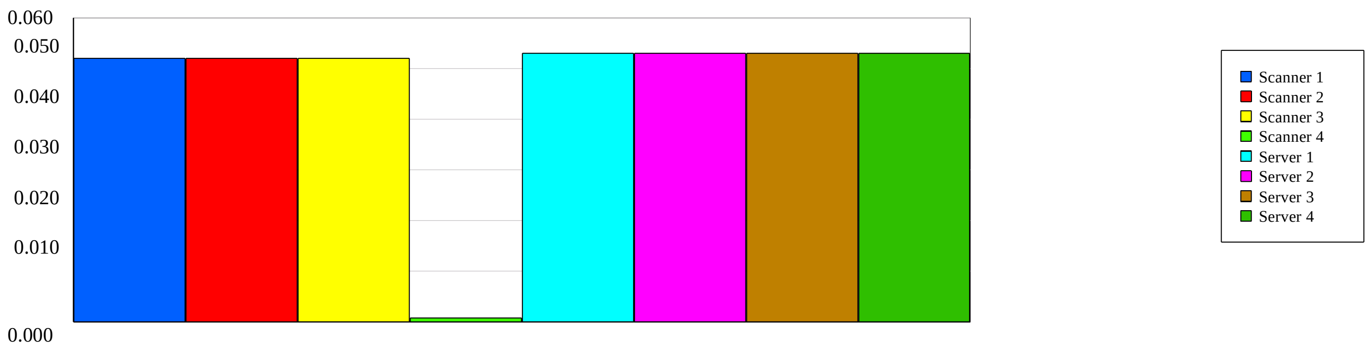
Airport Simulation

Replications: 100 Time Units: Minutes

Resource

Usage

Scheduled Utilization	Average	Half Width	Minimum Average	Maximum Average
Scanner 1	0.05205132	0.00	0.04984521	0.05393922
Scanner 2	0.05205132	0.00	0.04984521	0.05393922
Scanner 3	0.05205132	0.00	0.04984521	0.05393922
Scanner 4	0.00076118	0.00	0.00	0.00313006
Server 1	0.05305837	0.00	0.04253213	0.06834889
Server 2	0.05305837	0.00	0.04253213	0.06834889
Server 3	0.05305837	0.00	0.04253213	0.06834889
Server 4	0.05305837	0.00	0.04253213	0.06834889



Airport Simulation

Replications: 100 Time Units: Minutes

Resource

Usage

Total Number Seized	Average	Half Width	Minimum Average	Maximum Average
Scanner 1	100.00	0.00	100.00	100.00
Scanner 2	100.00	0.00	100.00	100.00
Scanner 3	100.00	0.00	100.00	100.00
Scanner 4	1.4800	0.35	0.00	6.0000
Server 1	100.00	0.00	100.00	100.00
Server 2	100.00	0.00	100.00	100.00
Server 3	100.00	0.00	100.00	100.00
Server 4	100.00	0.00	100.00	100.00