Data and Decision Making AT1-A

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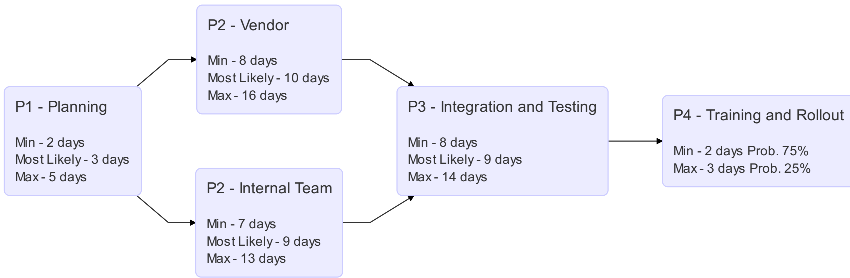
Libraries

```r
library(tidyverse)
library(DiagrammeR)
library(GoFKernel)
library(scales)
library(SimJoint)
library(Matrix)
```

Project Simulation Using Monte Carlo

Sequence Diagram

```r
# Create sequence graph

mermaid("
graph LR
  A(P1 - Planning<br><br><small>Min - 2 days<br>Most Likely - 3 days<br>Max - 5 days</small>)
  B(P2 - Vendor<br><br><small>Min - 8 days<br>Most Likely - 10 days<br>Max - 16 days</small>)
  C(P2 - Internal Team<br><br><small>Min - 7 days<br>Most Likely - 9 days<br>Max - 13 days</small>)
  D(P3 - Integration and Testing<br><br><small>Min - 8 days<br>Most Likely - 9 days<br>Max - 14 days</small>)
  E(P4 - Training and Rollout<br><br><small>Min - 2 days Prob. 75%<br>Max - 3 days Prob. 25%</small>)

  A-->B
  A-->C
  B-->D
  C-->D
  D-->E
  ")
```

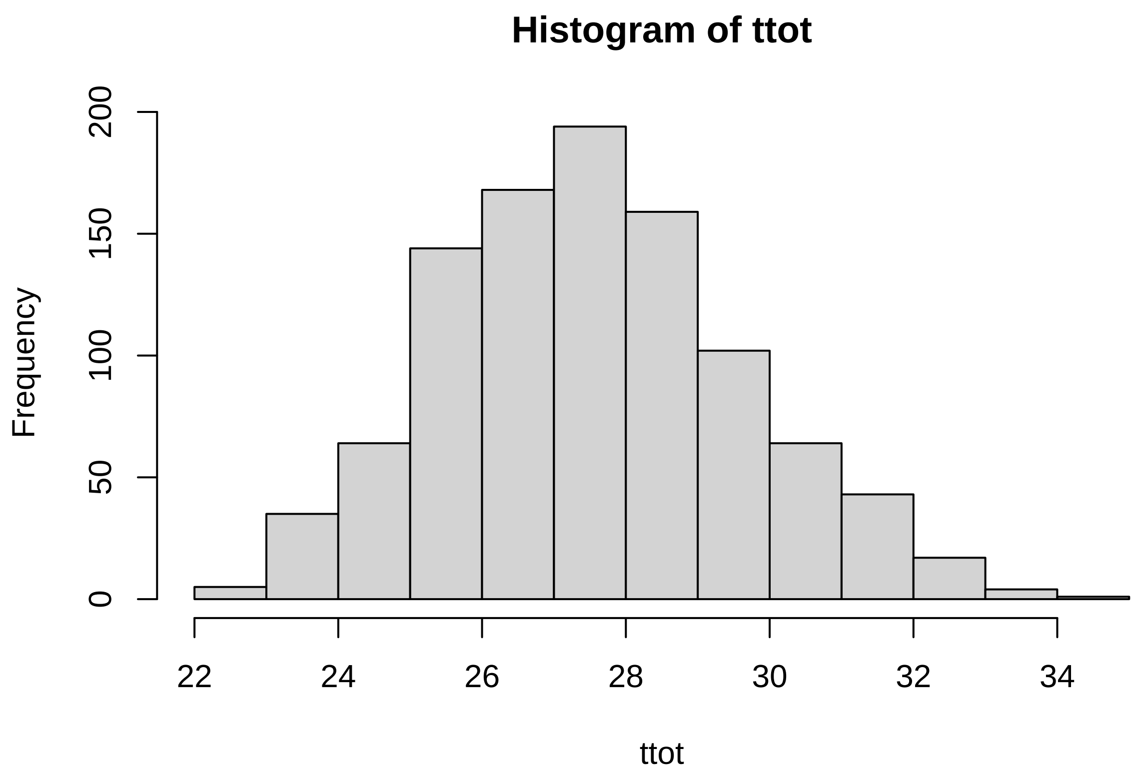


Simulation Using Triangular Distribution

```
# create data frame of tasks and times for the first 4 cases

task_durations <- data.frame(task = c("p1","p2v","p2i","p3"),
                             tmin = c(2,8,7,8),
                             tml  = c(3,10,9,9),
                             tmax = c(5,16,13,14))
```

```
## Monte Carlo Simulation with Triangle Distribution

# inverse triangle function

inv_triangle_cdf <- function(P, vmin, vml, vmax){

  Pvml <- (vml-vmin)/(vmax-vmin)

  return(ifelse(P < Pvml,
                vmin + sqrt(P*(vml-vmin)*(vmax-vmin)),
                vmax - sqrt((1-P)*(vmax-vml)*(vmax-vmin))))
}

# number of trials

n=1000

set.seed(98)

# trials df

tsim <- as.data.frame(matrix(nrow=n,ncol=nrow(task_durations)+1))

# for each task
```

```r
for (i in 1:nrow(task_durations)){
  #set task durations
  vmin <- task_durations$tmin[i]
  vml <- task_durations$tml[i]
  vmax <- task_durations$tmax[i]

  #generate n random numbers (one per trial)
  psim <- runif(n)
  #simulate n instances of task
  tsim[,i] <- inv_triangle_cdf(psim,vmin,vml,vmax)
}

# calc phase 4, likelyhood of being completed in 2 days 0.75 in 3 days 0.25
# Very naive, no interpolated distribution

tsim[,5] <- runif(nrow(tsim))
tsim[tsim[,5] < 0.25, 5] <- 3
tsim[tsim[,5] != 3, 5] <- 2

#sum costs for each trial
ttot <- tsim[,1] + pmax(tsim[,2], tsim[,3]) + tsim[,4] + tsim[,5]

#time distribution
hist(ttot)
```




```r
#mean, max, min and median time
mean(ttot)
```

```
## [1] 27.51006
```

```r
max(ttot)
```

```
## [1] 34.82005
```

```r
min(ttot)
```

```
## [1] 22.40172
```

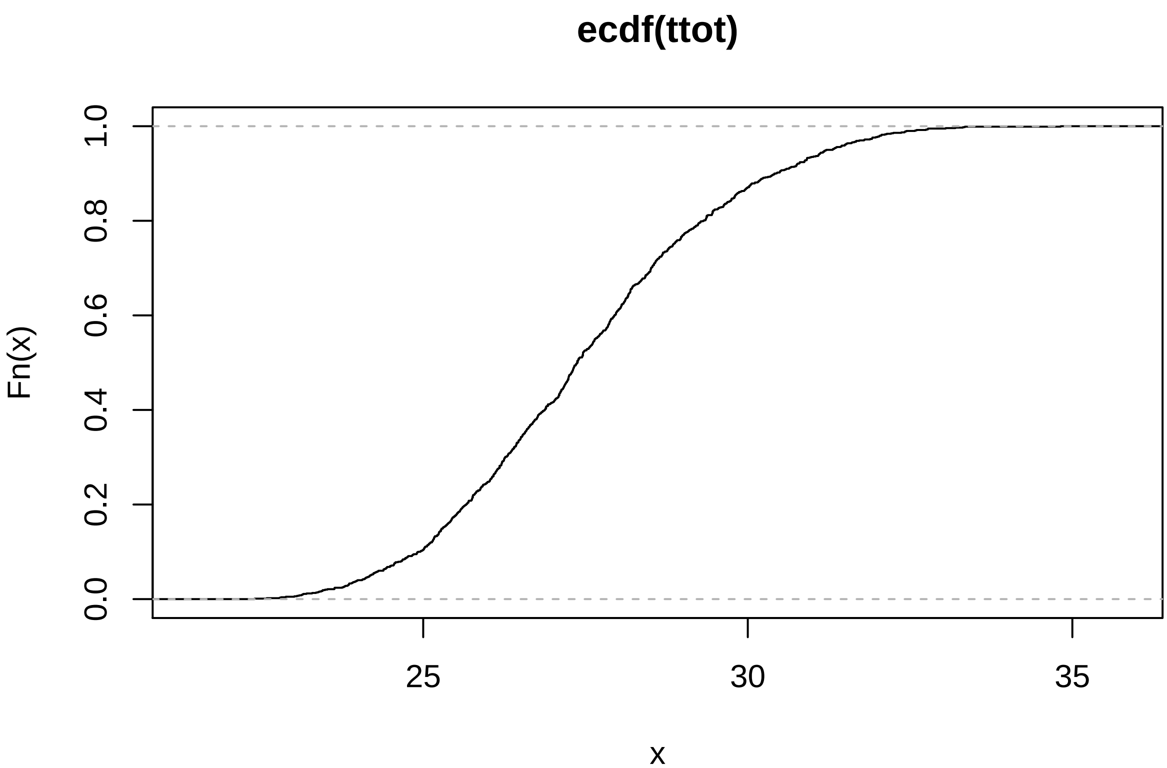
```r
median(ttot)
```

```
## [1] 27.37217
```

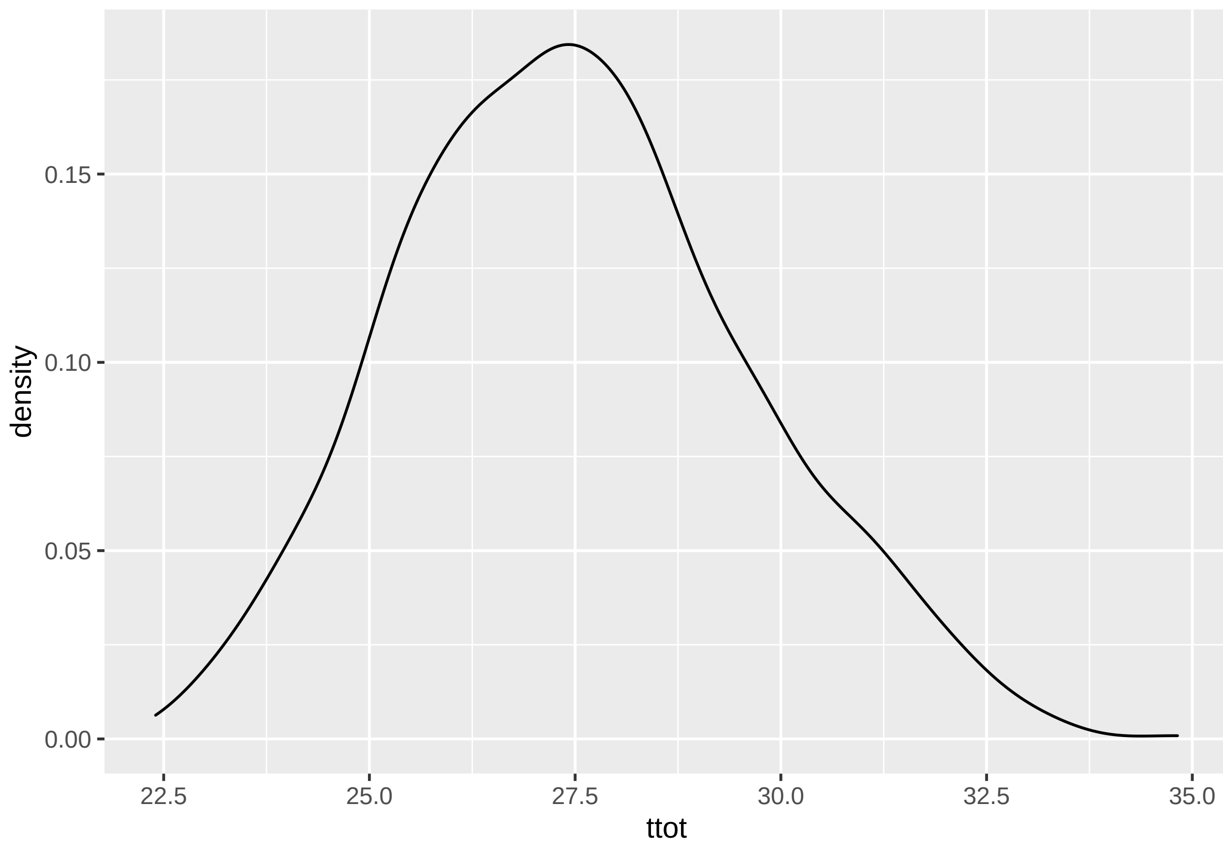
```r
#standard deviation
sd(ttot)
```

```
## [1] 2.107572
```

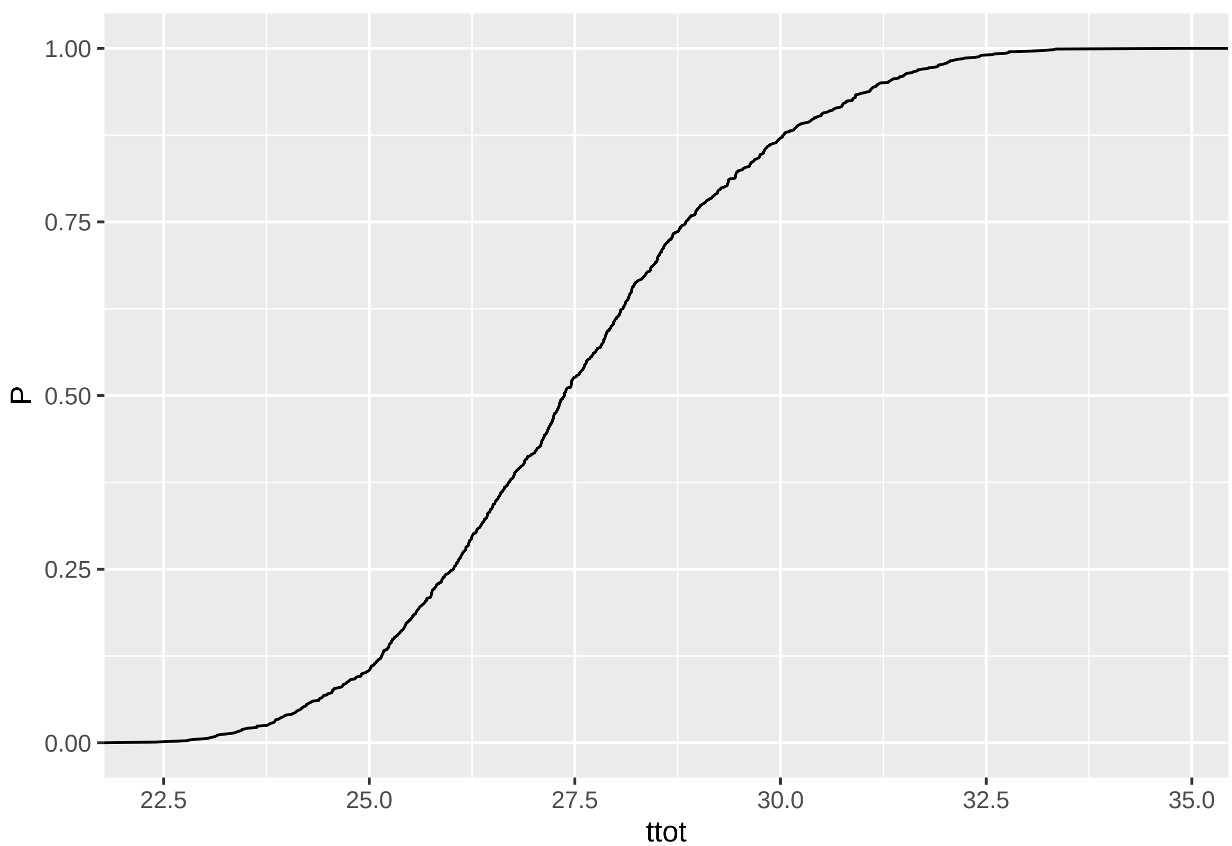
```r
#plot cdf
plot(ecdf(ttot))
```




```r
ggplot() + geom_density(aes(x = ttot))
```




```r
ggplot() + stat_ecdf(aes(x = ttot), geom = "line") + ylab("P")
```




```r
ecdf(ttot)(27)
```

```
## [1] 0.416
```

```r
quantile(ecdf(ttot),0.9,type=7)
```

```
##      90%
## 30.41336
```

```r
# why this type?
```

Distribution and assumption of indipendence are the model

Same probability for each time? No

Late / later

Improvements

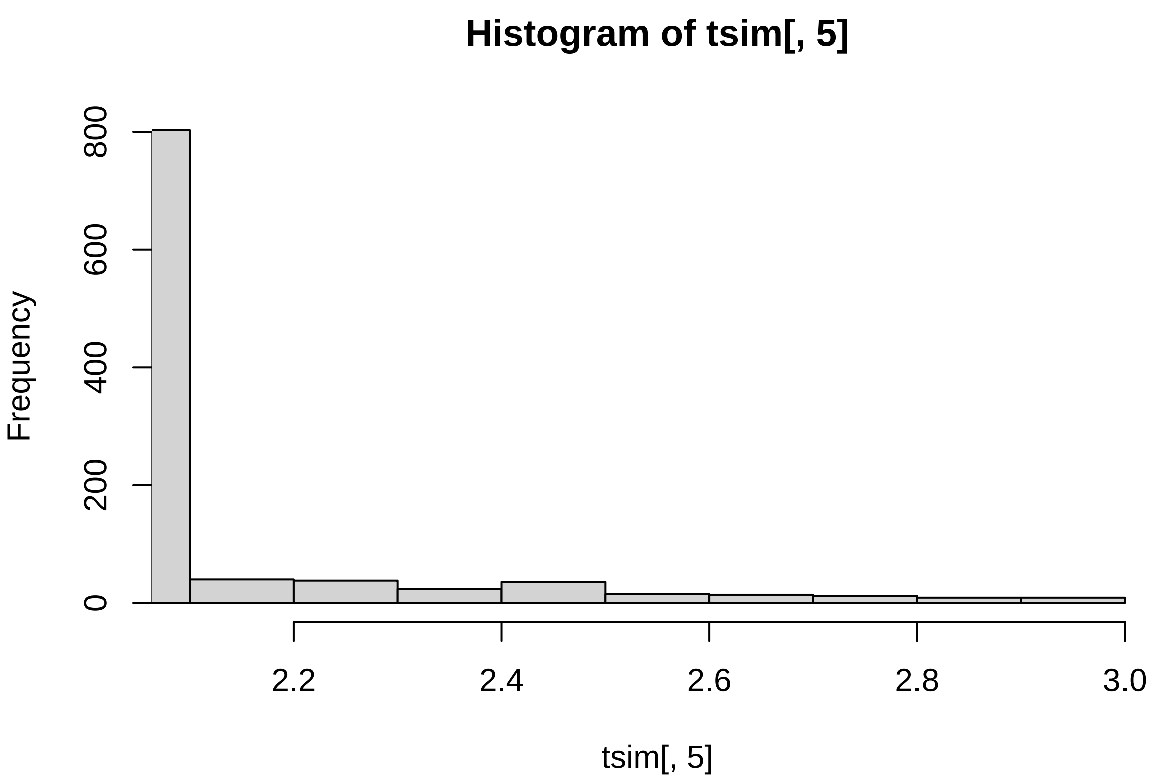
Impliment PERT Distribution

```r
# https://www.riskamp.com/beta-pert

rpert <- function( n, x.min, x.max, x.mode, lambda = 4 ){

    if( x.min > x.max || x.mode > x.max || x.mode < x.min ) stop( "invalid parameters" );

    x.range <- x.max - x.min;
    if( x.range == 0 ) return( rep( x.min, n ));

    mu <- ( x.min + x.max + lambda * x.mode ) / ( lambda + 2 );

    # special case if mu == mode
    if( mu == x.mode ){
        v <- ( lambda / 2 ) + 1
    }
    else {
        v <- (( mu - x.min ) * ( 2 * x.mode - x.min - x.max )) /
            (( x.mode - mu ) * ( x.max - x.min ));
    }

    w <- ( v * ( x.max - mu )) / ( mu - x.min );
    return ( rbeta( n, v, w ) * x.range + x.min );
}

pert <- rpert(1000, 7, 13, 9, lambda = 4)

# number of trials

n=1000

set.seed(98)

# trials df

tsim <- as.data.frame(matrix(nrow=n,ncol=nrow(task_durations)+1))

# for each task
for (i in 1:nrow(task_durations)){
  #set task durations
  vmin <- task_durations$tmin[i]
  vml <- task_durations$tml[i]
  vmax <- task_durations$tmax[i]

  #simulate n instances of task
```

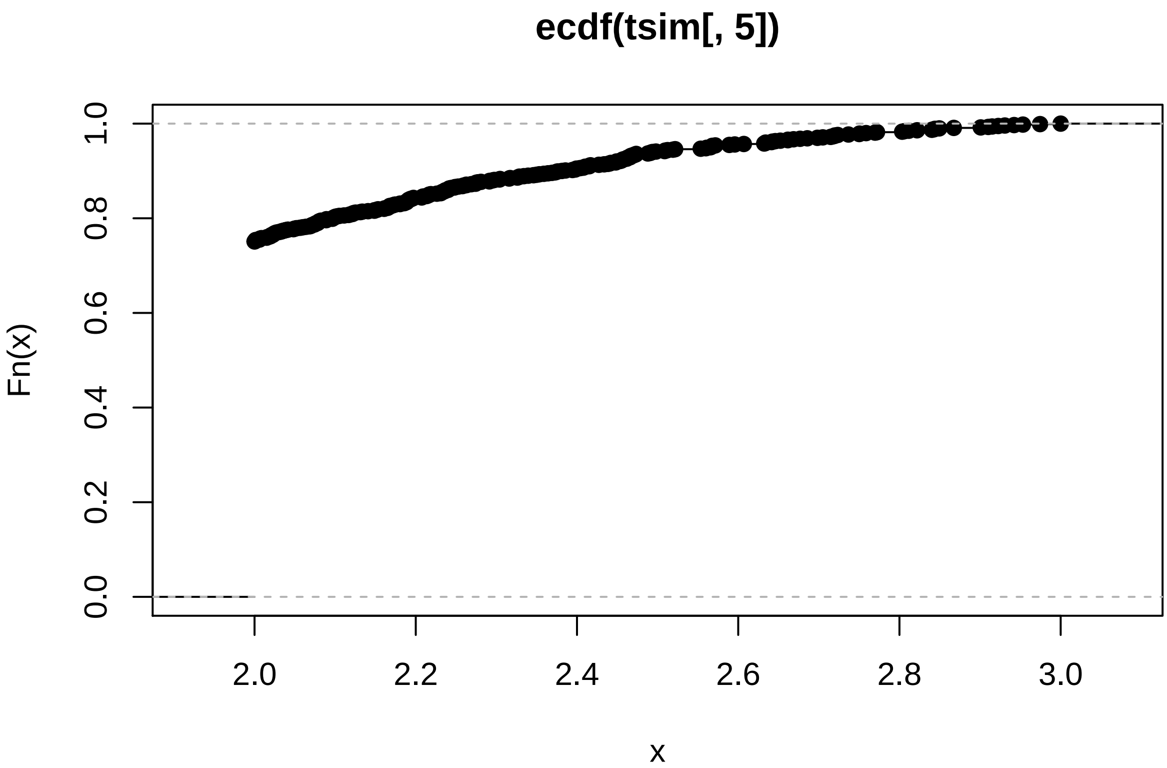
```
  tsim[,i] <- rpert(n,vmin,vmax,vml)
}
```

Improve phase 4 distribution

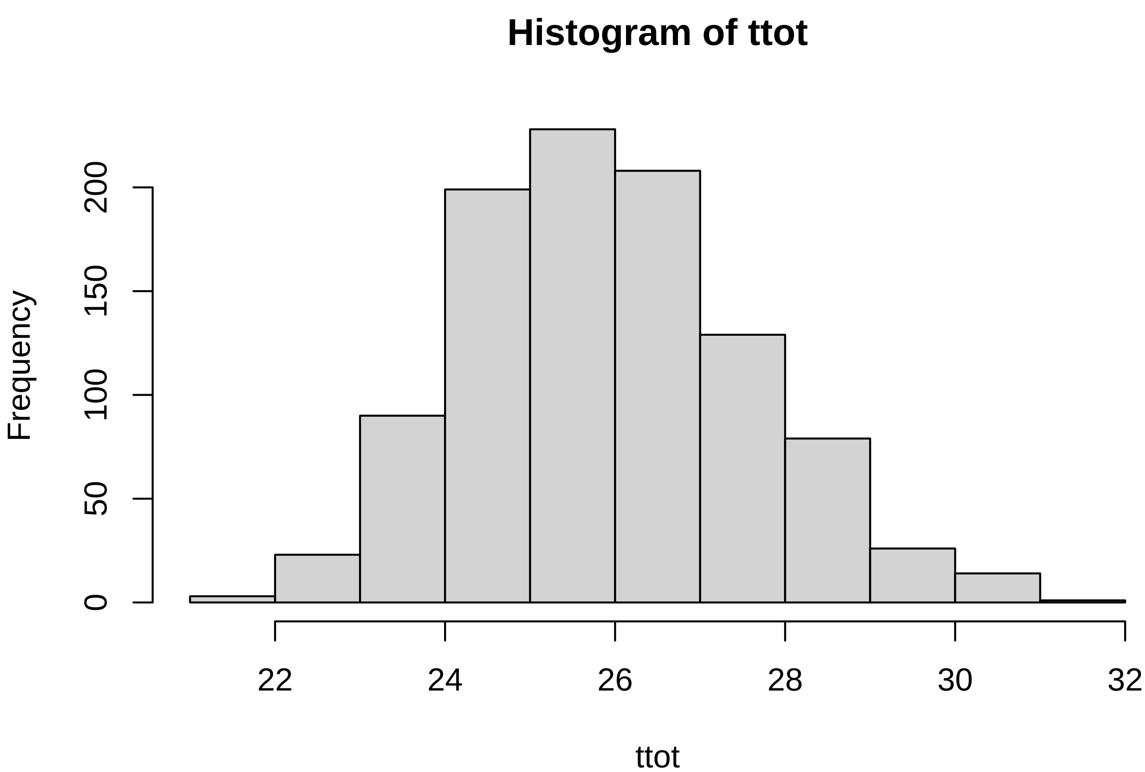
```
# calc phase 4, likelyhood of being completed in 2 days 0.75 in 3 days 0.25
# Very naive, no interpolated distribution

tsim[,5] <- rpert(nrow(tsim), 0, 1, 0.5, lambda = 4)
sfq <- quantile(ecdf(tsim[,5]),0.75,type=7)

tsim[tsim[,5] <= sfq, 5] <- 2
tsim[tsim[,5] != 2, 5] <- rescale(tsim[tsim[,5] != 2, 5], to = c(2:3))
hist(tsim[,5], xlim = c(2.1,3))
```




```
plot(ecdf(tsim[,5]))
```




```r
#sum costs for each trial
ttot <- tsim[,1] + pmax(tsim[,2], tsim[,3]) + tsim[,4] + tsim[,5]

#time distribution
hist(ttot)
```



```
#mean, max, min and median time
mean(ttot)
```

```
## [1] 25.92015
```

```
max(ttot)
```

```
## [1] 31.10815
```

```
min(ttot)
```

```
## [1] 21.25254
```

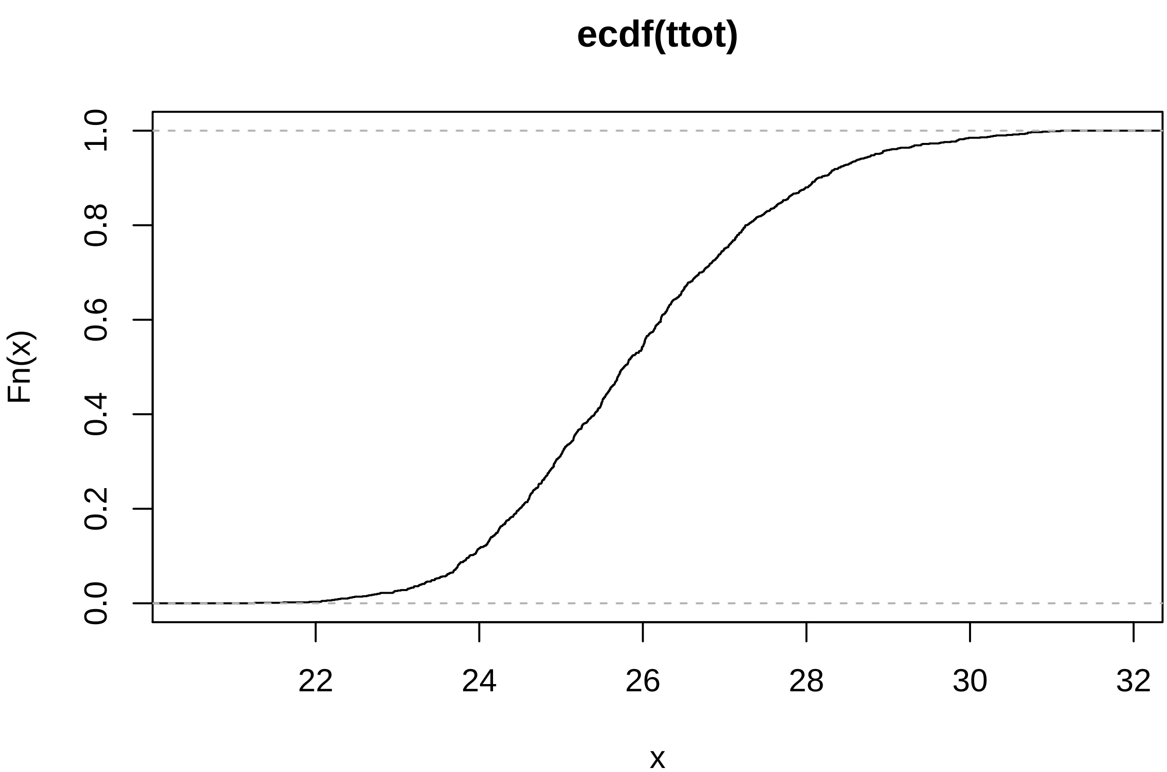
```
median(ttot)
```

```
## [1] 25.76896
```

```
#standard deviation
sd(ttot)
```

```
## [1] 1.67448
```

```
#plot cdf
plot(ecdf(ttot))
```



#late-later correlation

```
cor(tsim)
```

```
##              V1           V2          V3           V4           V5
## V1  1.000000000 -0.049728980 -0.08467255 -0.009272618  0.055813332
## V2 -0.049728980  1.000000000  0.00371570 -0.037924524  0.005817681
## V3 -0.084672548  0.003715700  1.00000000 -0.011781751 -0.012800199
## V4 -0.009272618 -0.037924524 -0.01178175  1.000000000 -0.023429134
## V5  0.055813332  0.005817681 -0.01280020 -0.023429134  1.000000000
```

```
set.seed(98)
cormat <- matrix(runif(25, min = 0.4, max = 0.6), nrow = 5, ncol = 5)
```

```r
for (i in 1:nrow(cormat)) {
cormat[i,i] <- 1
}

cormat <- as.matrix(forceSymmetric(cormat))

cormat
```

```
##           [,1]      [,2]      [,3]      [,4]      [,5]
## [1,] 1.0000000 0.4621269 0.5718670 0.5787514 0.5419149
## [2,] 0.4621269 1.0000000 0.5548362 0.4568522 0.4744907
## [3,] 0.5718670 0.5548362 1.0000000 0.4538582 0.5309327
## [4,] 0.5787514 0.4568522 0.4538582 1.0000000 0.5985139
## [5,] 0.5419149 0.4744907 0.5309327 0.5985139 1.0000000
```

```r
tsimcor <- tsim %>%
  map_df(sort) %>%
  as.matrix()

tsimcor <- SJpearson(tsimcor, cormat)$X
```

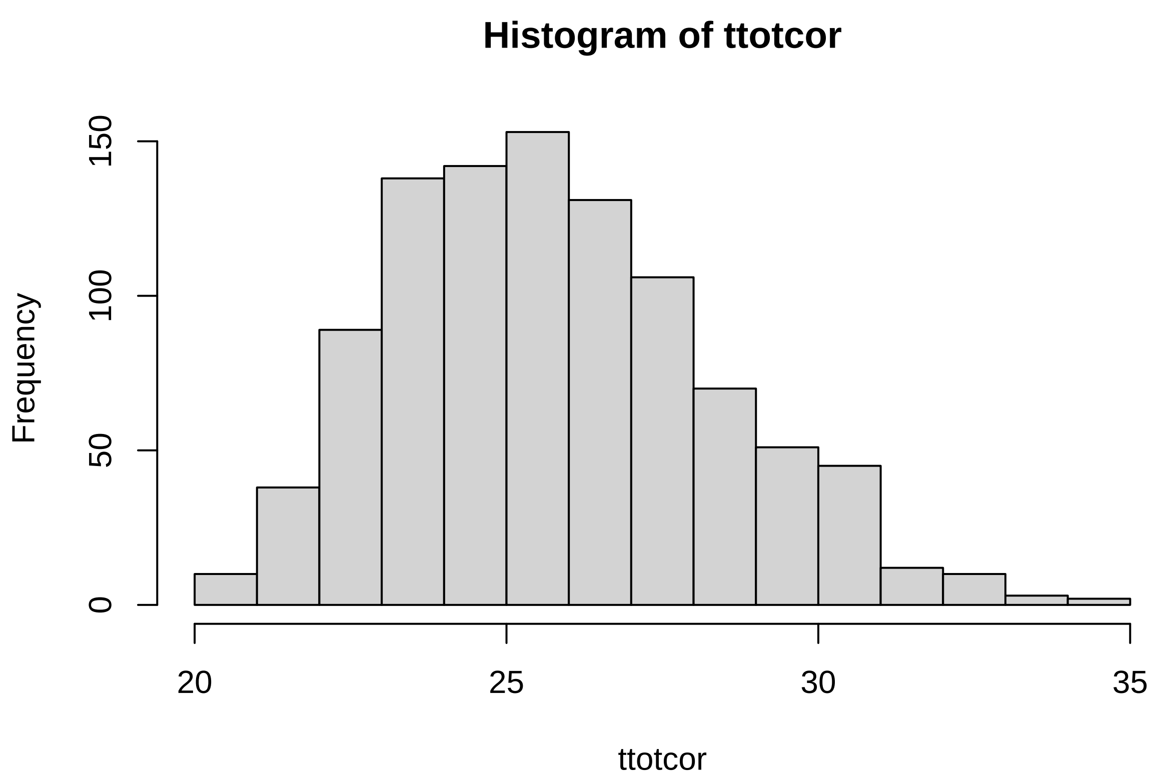
```
## Iteration = 1: square root of mean squared error in cor = 0.161425
## Cholesky decomposition failed. Perform eigen decomposition.
## Iteration = 2: square root of mean squared error in cor = 0.181728
## Iteration = 3: square root of mean squared error in cor = 0.0437117
## Iteration = 4: square root of mean squared error in cor = 0.0134497
## Iteration = 5: square root of mean squared error in cor = 0.00407298
## Iteration = 6: square root of mean squared error in cor = 0.00137905
## Iteration = 7: square root of mean squared error in cor = 0.000570315
## Iteration = 8: square root of mean squared error in cor = 8.90303e-05
## Iteration = 9: square root of mean squared error in cor = 9.0728e-05
## Iteration = 10: square root of mean squared error in cor = 0.000101371
## Iteration = 11: square root of mean squared error in cor = 8.45253e-05
## Iteration = 12: square root of mean squared error in cor = 9.12067e-05
## Iteration = 13: square root of mean squared error in cor = 8.41472e-05
## Iteration = 14: square root of mean squared error in cor = 0.000118192
## Iteration = 15: square root of mean squared error in cor = 8.95425e-05
## Iteration = 16: square root of mean squared error in cor = 5.64741e-05
## Iteration = 17: square root of mean squared error in cor = 4.0099e-05
## Iteration = 18: square root of mean squared error in cor = 9.10892e-05
## Iteration = 19: square root of mean squared error in cor = 4.46935e-05
## Iteration = 20: square root of mean squared error in cor = 3.58392e-05
## Iteration = 21: square root of mean squared error in cor = 4.61948e-05
## Iteration = 22: square root of mean squared error in cor = 2.18622e-05
## Iteration = 23: square root of mean squared error in cor = 4.86942e-05
## Iteration = 24: square root of mean squared error in cor = 3.48945e-05
## Iteration = 25: square root of mean squared error in cor = 3.48945e-05
## Iteration = 26: square root of mean squared error in cor = 2.18622e-05
## Iteration = 27: square root of mean squared error in cor = 2.18622e-05
## Iteration = 28: square root of mean squared error in cor = 2.18622e-05
## Iteration = 29: square root of mean squared error in cor = 2.18622e-05
## Iteration = 30: square root of mean squared error in cor = 2.18622e-05
## Iteration = 31: square root of mean squared error in cor = 2.18622e-05
## Iteration = 32: square root of mean squared error in cor = 2.18622e-05
## Iteration = 33: square root of mean squared error in cor = 2.18622e-05
```

```r
tsimcor <- as.data.frame(tsimcor)
cor(tsimcor)
```

```
##           V1        V2        V3        V4        V5
## V1 1.0000000 0.4621277 0.5718675 0.5787463 0.5419289
## V2 0.4621277 1.0000000 0.5548265 0.4568448 0.4744661
```

```
## V3 0.5718675 0.5548265 1.0000000 0.4538334 0.5308765
## V4 0.5787463 0.4568448 0.4538334 1.0000000 0.5985199
## V5 0.5419289 0.4744661 0.5308765 0.5985199 1.0000000
```

```
#sum costs for each trial
ttotcor <- tsimcor[,1] + pmax(tsimcor[,2], tsimcor[,3]) + tsimcor[,4] + tsimcor[,5]

#time distribution
hist(ttotcor)
```




```
#mean, max, min and median time
mean(ttotcor)
```

```
## [1] 25.76437
```

```
max(ttotcor)
```

```
## [1] 34.15506
```

```
min(ttotcor)
```

```
## [1] 20.35091
```

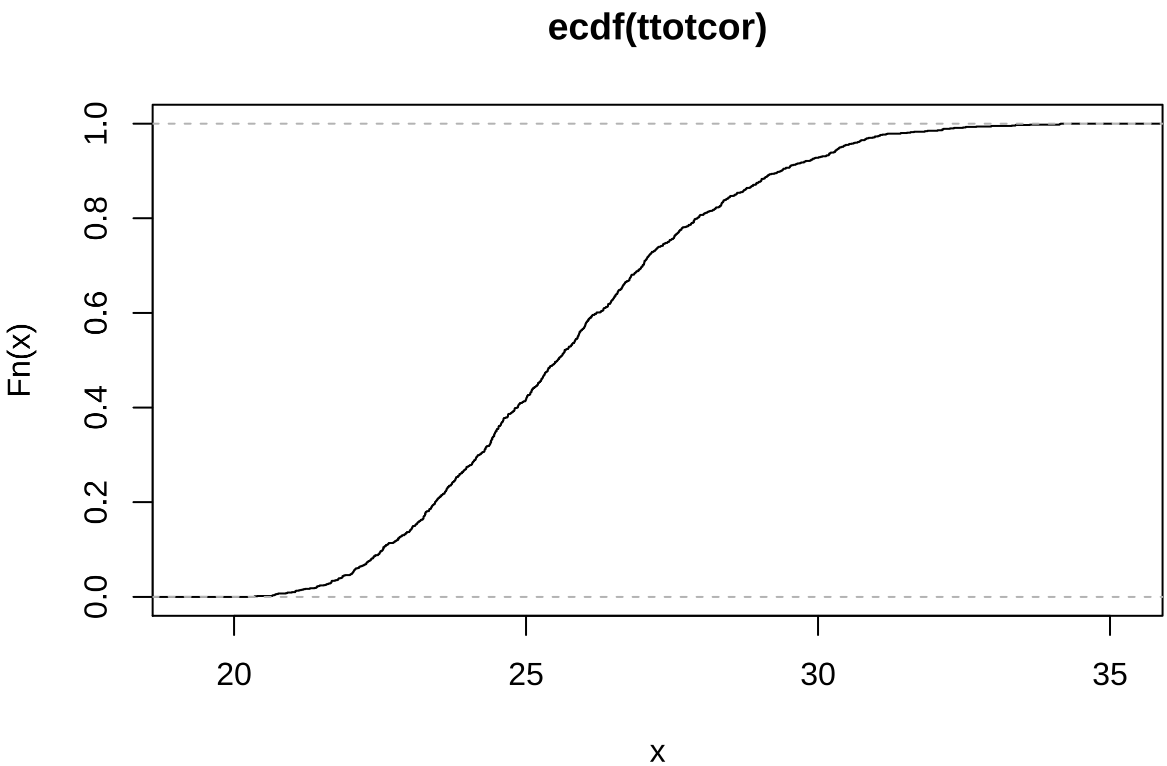
```
median(ttotcor)
```

```
## [1] 25.54177
```

```
#standard deviation
sd(ttotcor)
```

```
## [1] 2.575265
```

```
#plot cdf
plot(ecdf(ttotcor))
```



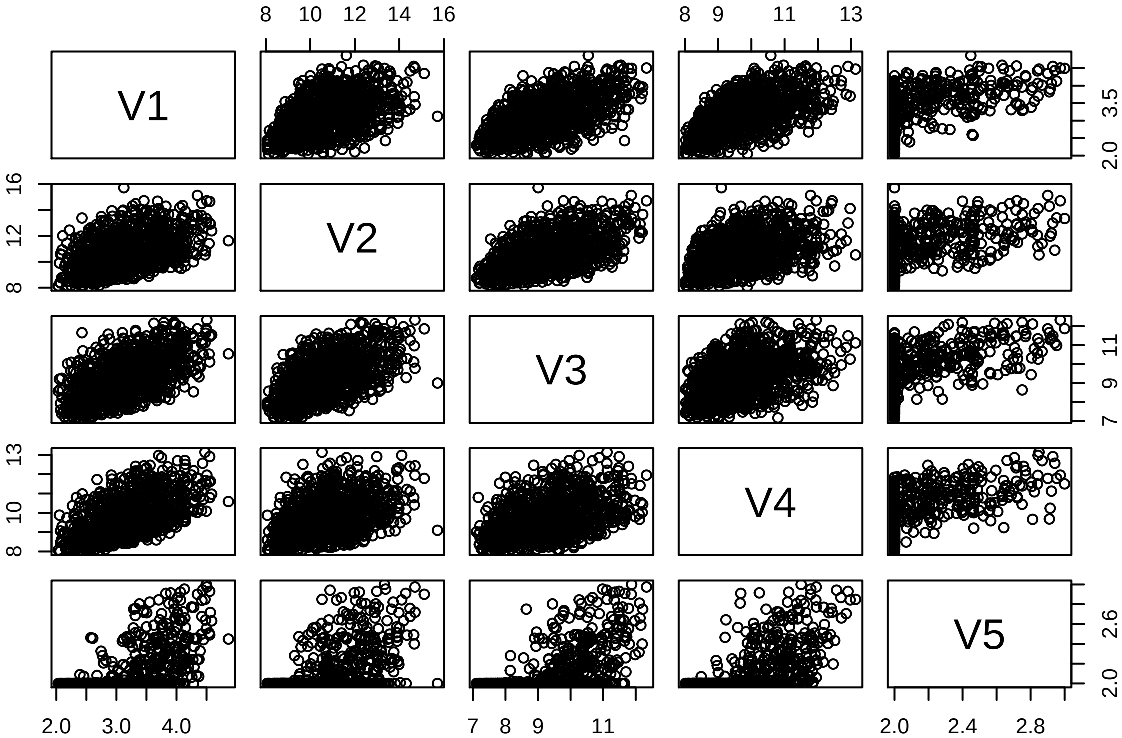

```
ecdf(ttotcor)(27)
```

```
## [1] 0.701
```

```
quantile(ecdf(ttotcor),0.9,type=7)
```

```
##      90%
## 29.36257
```

```
pairs(tsimcor)
```


V1
V2
V3
V4
V5
8
10
12
14
16
9
11
13
3.5
2.0
7
2.6
2.4
2.8
3.0
4.0