Data Exploration

Nathan Shepherd

2022-04-03

```
library(readr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ggplot2)
library(FactoMineR) # PCA
```

```
rand_dat <- read_csv("../utils/rand_state_acts.csv",show_col_types = FALSE)
names(rand_dat)
```

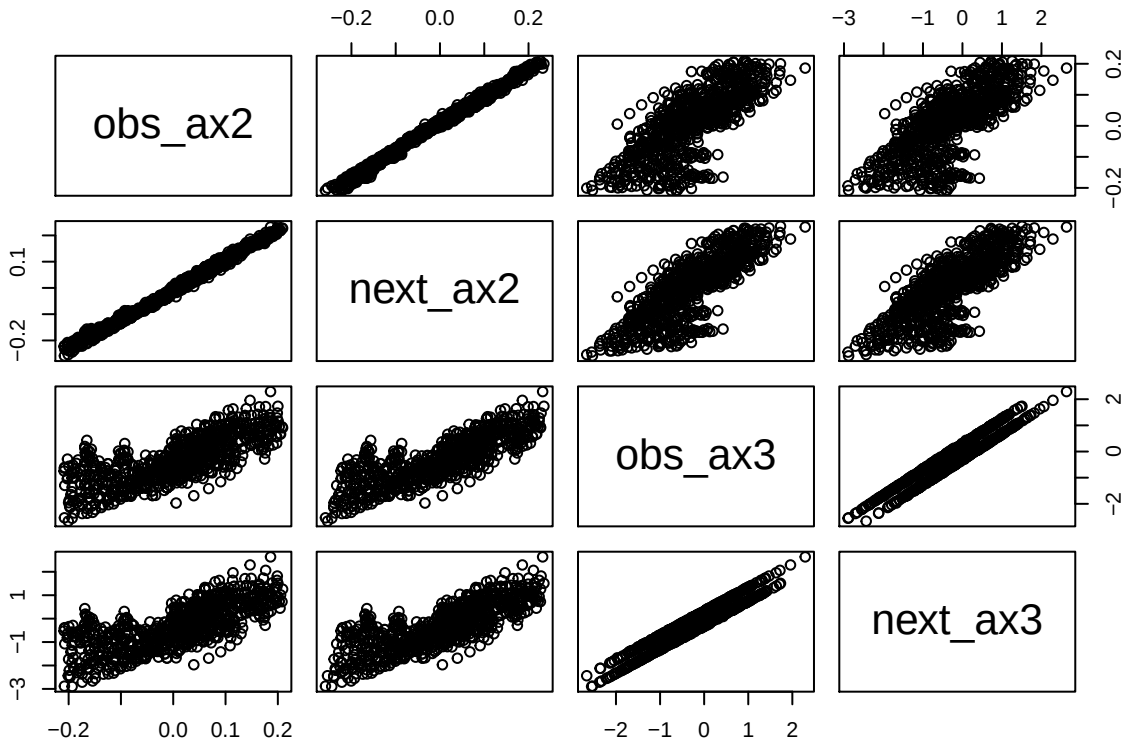
```
##  [1] "timestep" "episode"  "reward"   "act"      "obs_ax0"  "next_ax0"
##  [7] "obs_ax1"  "next_ax1" "obs_ax2"  "next_ax2" "obs_ax3"  "next_ax3"
```

```
summary(rand_dat)
```

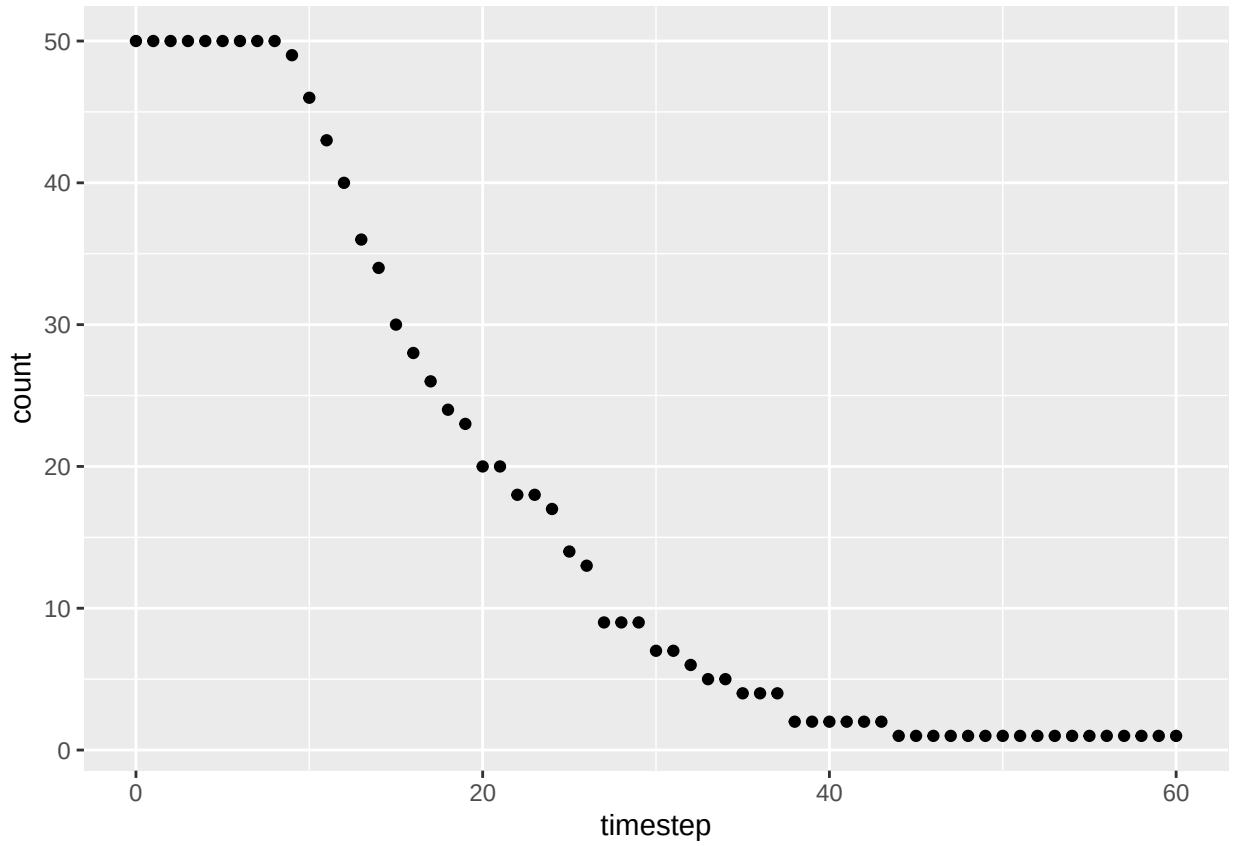
```
##     timestep        episode          reward           act
##  Min.   : 0.00   Min.   : 0.00   Min.   : 9.00   Min.   :0.0000
##  1st Qu.: 5.00   1st Qu.:14.00   1st Qu.:16.00   1st Qu.:0.0000
##  Median :10.00   Median :26.00   Median :25.00   Median :1.0000
##  Mean   :12.46   Mean   :25.53   Mean   :25.92   Mean   :0.5568
##  3rd Qu.:18.00   3rd Qu.:36.00   3rd Qu.:32.00   3rd Qu.:1.0000
##  Max.   :60.00   Max.   :49.00   Max.   :61.00   Max.   :1.0000
##     obs_ax0              next_ax0           obs_ax1            next_ax1
##  Min.   :-0.1096541   Min.   :-0.12996   Min.   :-1.40519   Min.   :-1.6015
##  1st Qu.:-0.0156297   1st Qu.:-0.01832   1st Qu.:-0.06116   1st Qu.:-0.2266
##  Median :-0.0000219   Median : 0.00432   Median : 0.16127   Median : 0.1625
##  Mean   : 0.0242654   Mean   : 0.02875   Mean   : 0.22419   Mean   : 0.2461
##  3rd Qu.: 0.0597766   3rd Qu.: 0.07109   3rd Qu.: 0.55266   3rd Qu.: 0.5563
##  Max.   : 0.5181503   Max.   : 0.55580   Max.   : 1.88238   Max.   : 2.0789
##     obs_ax2            next_ax2           obs_ax3           next_ax3
##  Min.   :-0.20863   Min.   :-0.25873   Min.   :-2.6632   Min.   :-2.8973
##  1st Qu.:-0.03345   1st Qu.:-0.05214   1st Qu.:-0.7747   1st Qu.:-0.8118
##  Median : 0.03682   Median : 0.03486   Median :-0.1940   Median :-0.2275
##  Mean   : 0.01503   Mean   : 0.01036   Mean   :-0.2336   Mean   :-0.2620
##  3rd Qu.: 0.06781   3rd Qu.: 0.07017   3rd Qu.: 0.3324   3rd Qu.: 0.3572
```

```
##  Max.   : 0.20913   Max.   : 0.23477   Max.   : 2.2920   Max.   : 2.6358
```

```
pairs(rand_dat[9:12])
```




```
by_timestep = rand_dat %>% group_by(timestep)
timestep_summ = summarize(by_timestep, count=n(), avg.reward=mean(reward))
ggplot(timestep_summ, aes(x=timestep, y=count)) + geom_point()
```

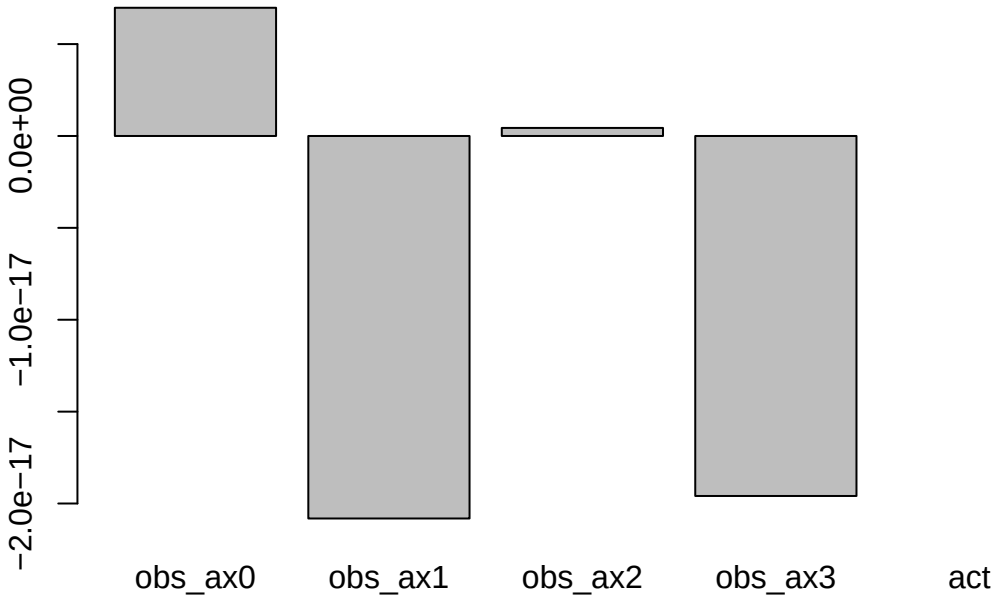



```
# Determine obs_axis with greatest difference for observation given the action
states = rand_dat %>% select(obs_ax0,obs_ax1,obs_ax2,obs_ax3,act)
sact0 = states %>% filter(act==0) %>% scale() %>% colMeans(na.rm = TRUE)
sact1 = states %>% filter(act==1) %>% scale() %>% colMeans(na.rm = TRUE)

sact0 - sact1
```

```
##       obs_ax0       obs_ax1       obs_ax2       obs_ax3           act
##  6.976043e-18 -2.081486e-17  4.376055e-19 -1.958966e-17           NaN
```

```
barplot(sact0 - sact1)
```



Exploratory Factor Analysis

```
# Maximum Likelihood Factor Analysis
# entering raw data and extracting 3 factors,
# with varimax rotation
mydata = states[1:4] # drop act
fit <- factanal(mydata, 1, rotation="varimax")
print(fit, digits=2, cutoff=.3, sort=TRUE)
```

```
##
## Call:
## factanal(x = mydata, factors = 1, rotation = "varimax")
##
## Uniquenesses:
## obs_ax0 obs_ax1 obs_ax2 obs_ax3
##    0.52    0.07    0.45    0.00
##
## Loadings:
## [1] -0.70 -0.96  0.74  1.00
##
##                Factor1
## SS loadings       2.96
## Proportion Var    0.74
##
## Test of the hypothesis that 1 factor is sufficient.
## The chi square statistic is 2763.4 on 2 degrees of freedom.
## The p-value is 0
```

```
# plot factor 1 by factor 2
#load <- fit$loadings[,1:2]
#plot(load,type="n") # set up plot
#text(load,labels=names(mydata),cex=.7) # add variable names
```

```
# fraction of the variable's total variance explained by the factor
apply(fit$loadings^2, 1, sum)
```

```
##   obs_ax0   obs_ax1   obs_ax2   obs_ax3
## 0.4842480 0.9286341 0.5504226 0.9950522
```

```
Lambda <- fit$loadings
Psi <- diag(fit$uniquenesses)
S <- fit$correlation
Sigma <- Lambda %*% t(Lambda) + Psi
# residual matrix. Numbers close to 0 indicate that our factor model is a good representation of the un
round(S - Sigma, 6)
```

```
##           obs_ax0   obs_ax1   obs_ax2   obs_ax3
## obs_ax0  0.000000  0.035391 -0.295516  0.004840
## obs_ax1  0.035391  0.000000  0.105078 -0.000630
## obs_ax2 -0.295516  0.105078  0.000000  0.005113
## obs_ax3  0.004840 -0.000630  0.005113 -0.000052
```

```
reg_fit <- factanal(mydata, factors = 1, scores = "regression")
mean(reg_fit$scores)
```

```
## [1] -9.26356e-18
```

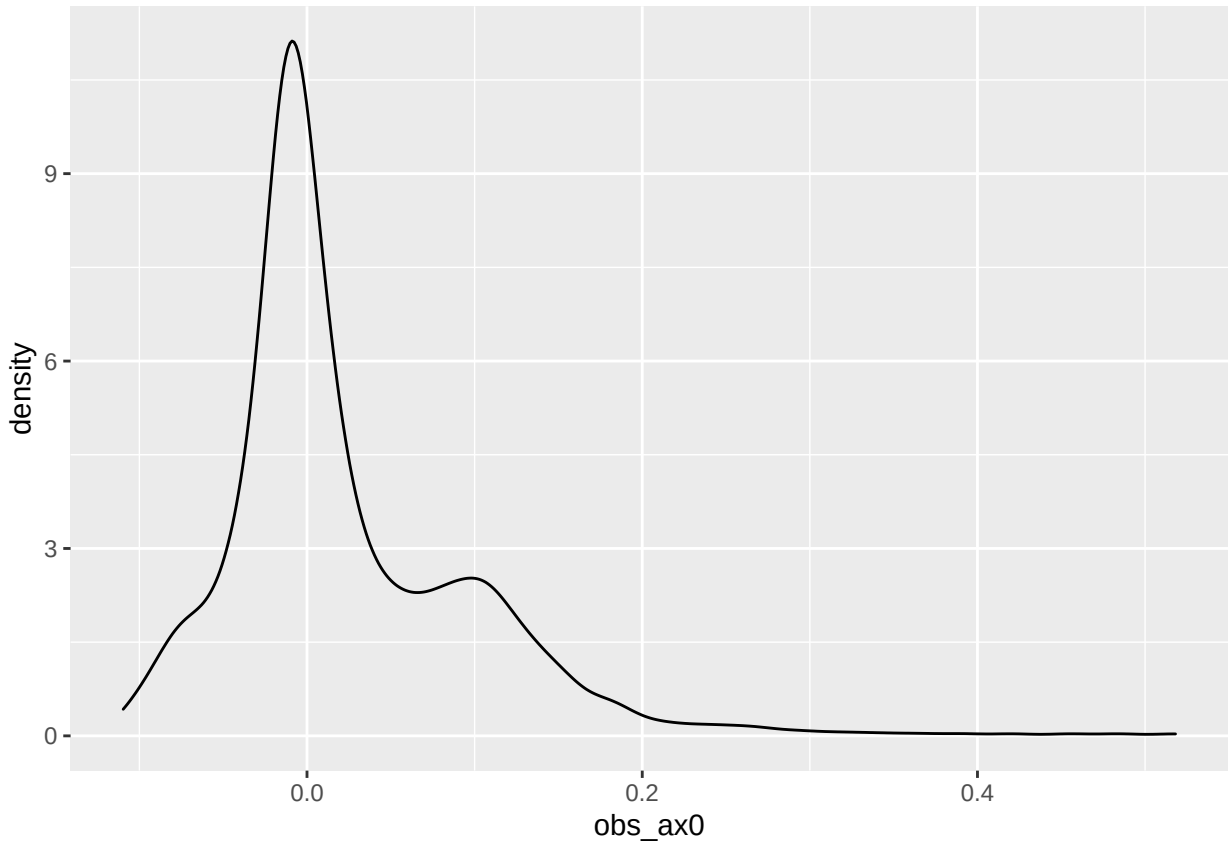
```
sd(reg_fit$scores)
```

```
## [1] 0.9976737
```

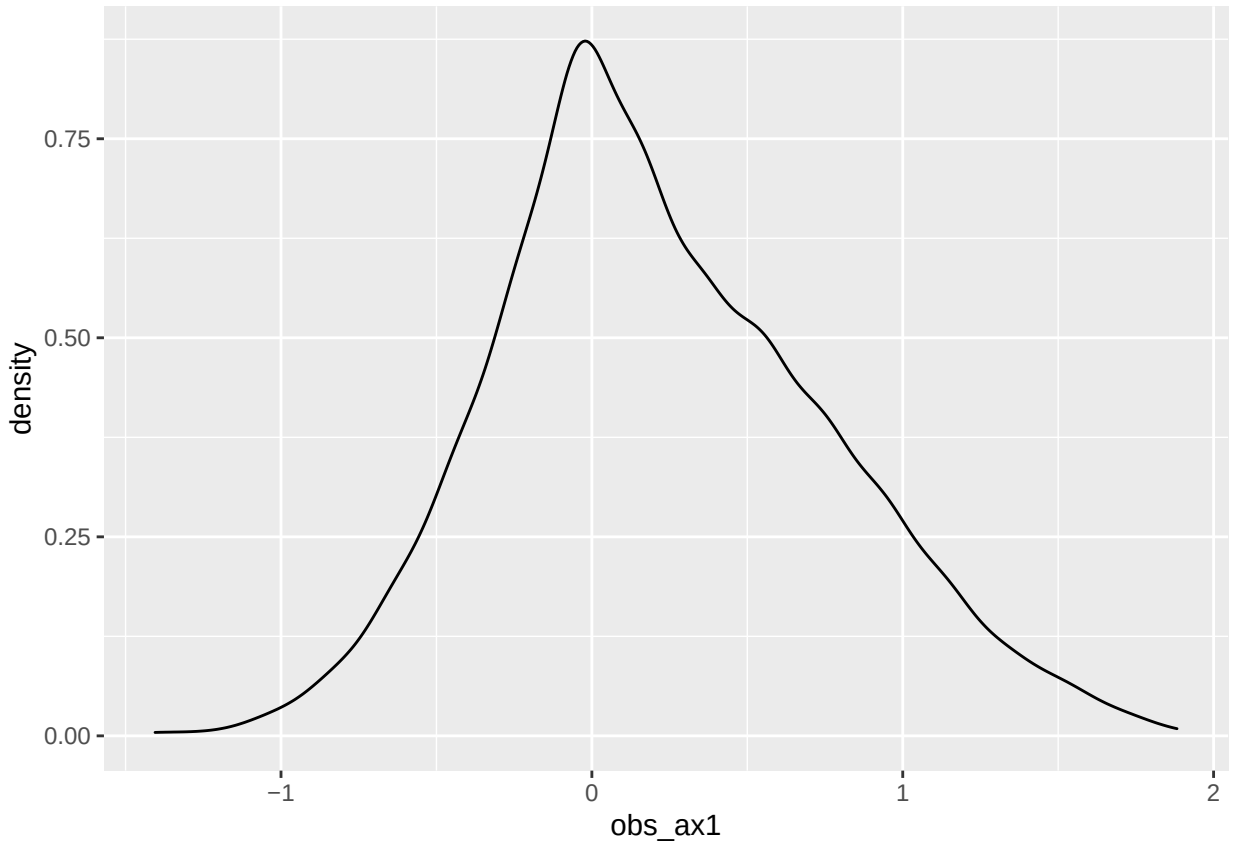
```
reg_fit$loadings
```

```
##
## Loadings:
##         Factor1
## obs_ax0 -0.696
## obs_ax1 -0.964
## obs_ax2  0.742
## obs_ax3  0.998
##
##                Factor1
## SS loadings      2.958
## Proportion Var   0.740
```

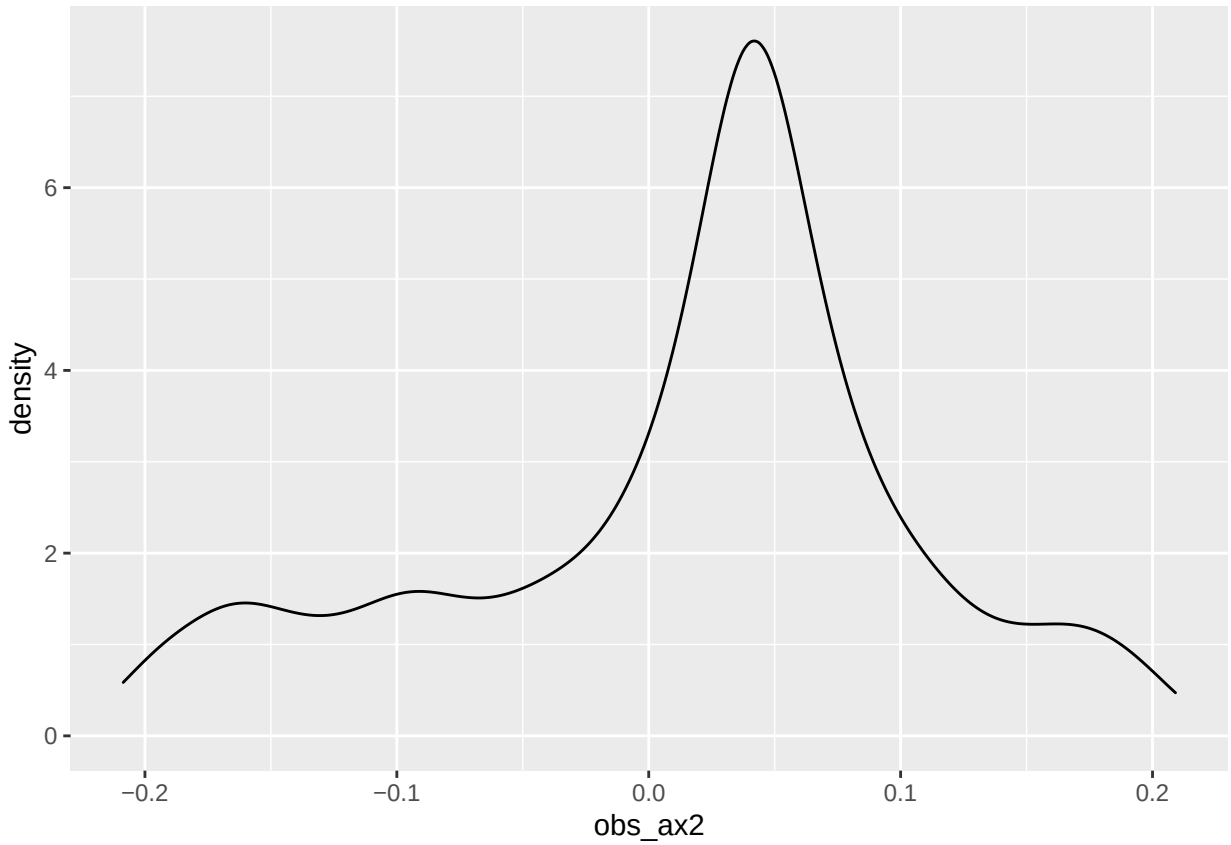
```
ggplot(states, aes(obs_ax0)) + geom_density()
```



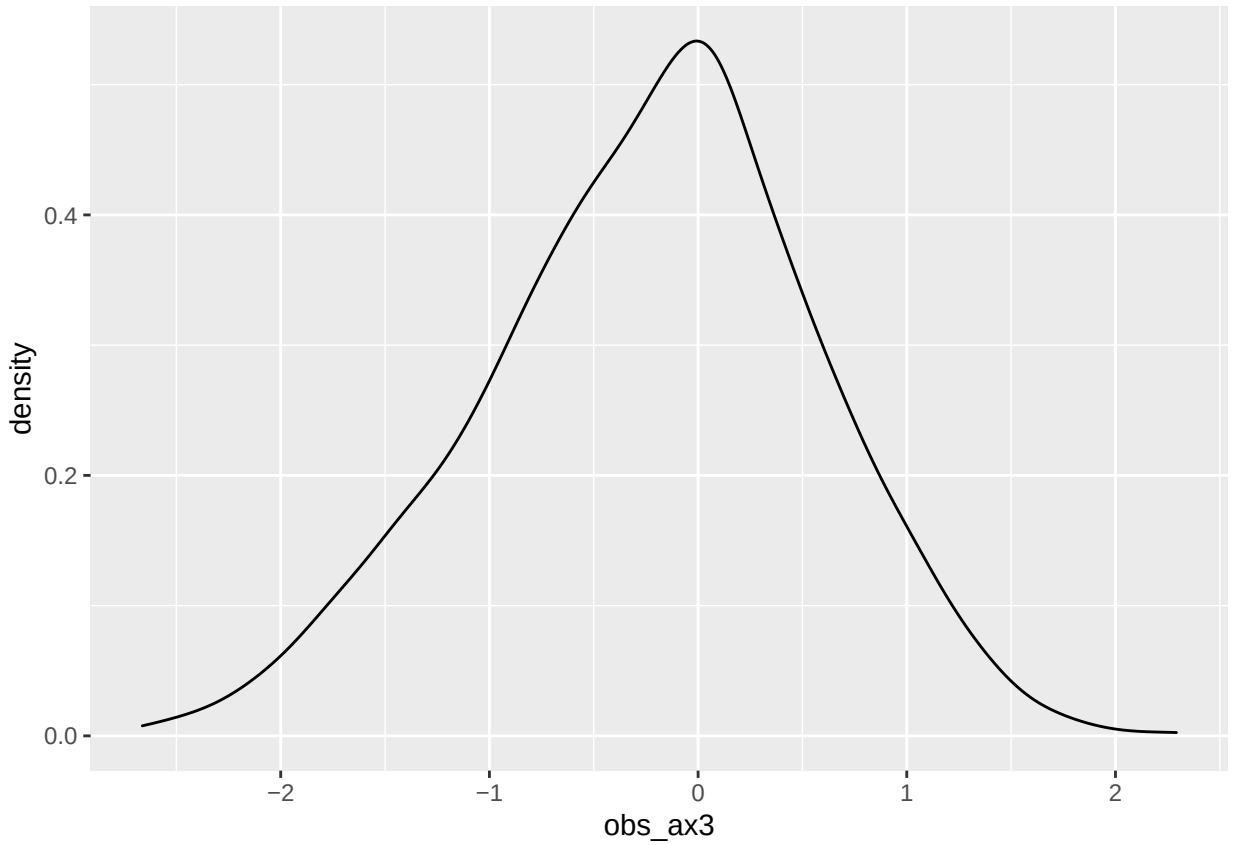

```
ggplot(states, aes(obs_ax1)) + geom_density()
```



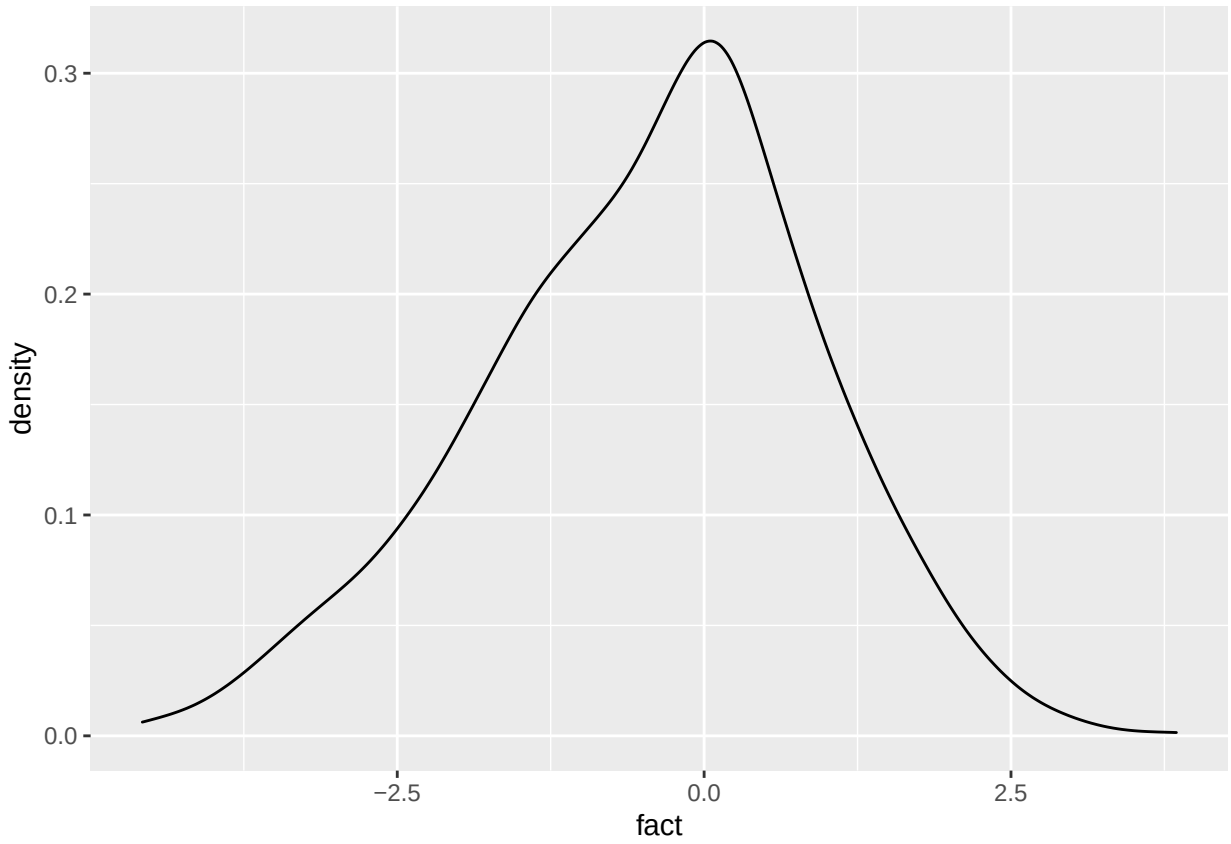

```
ggplot(states, aes(obs_ax2)) + geom_density()
```



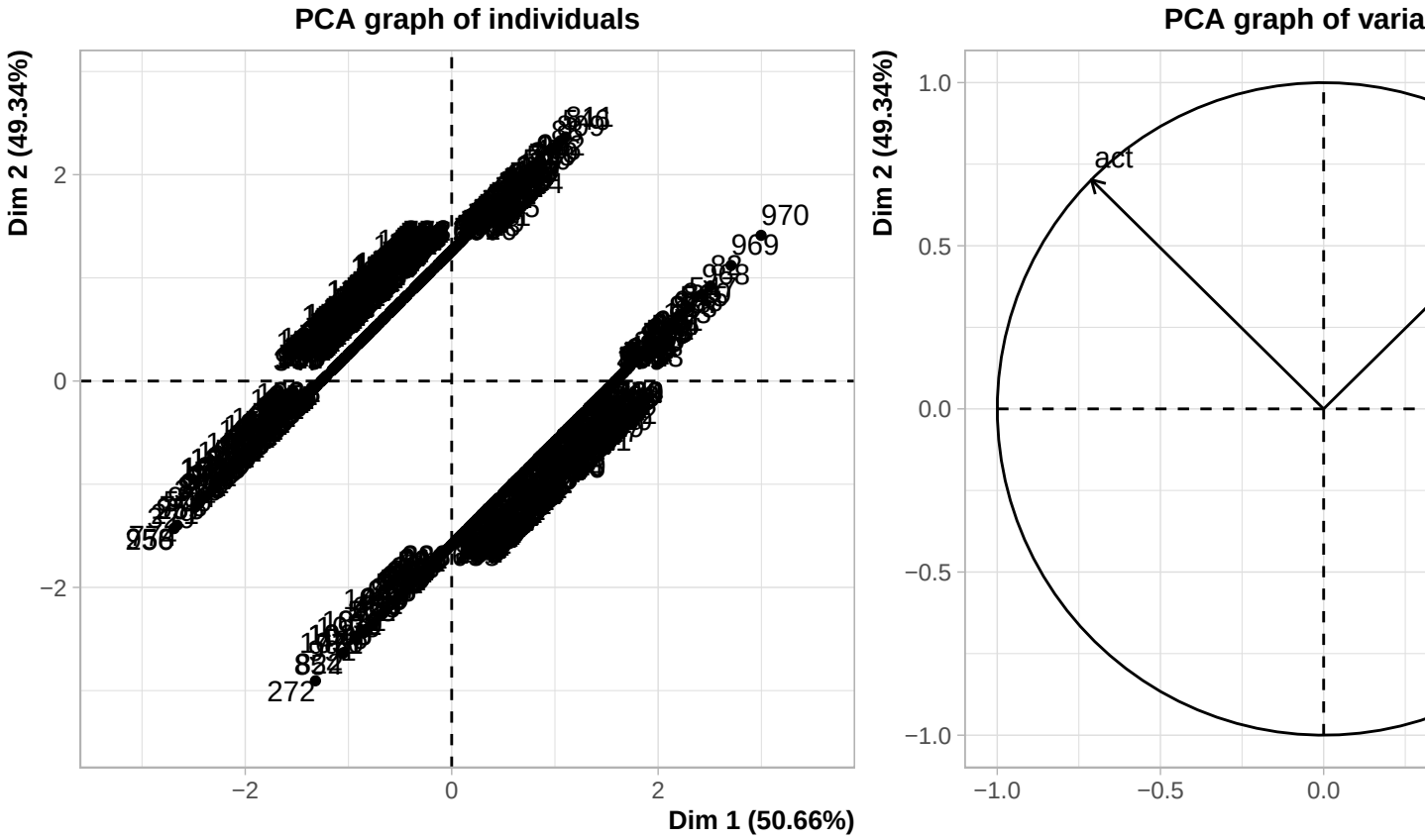

```
ggplot(states, aes(obs_ax3)) + geom_density()
```



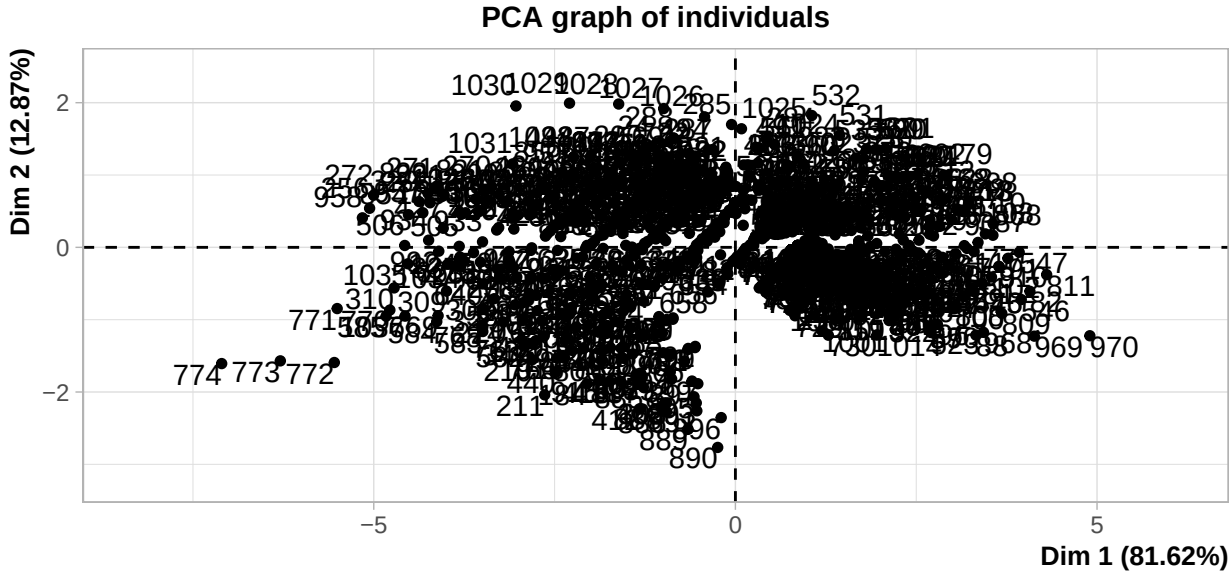

```
data_factor = data.frame(as.matrix(mydata) %*% matrix(fit$loadings))
names(data_factor) = c("fact")
ggplot(data_factor, aes(fact)) + geom_density()
```

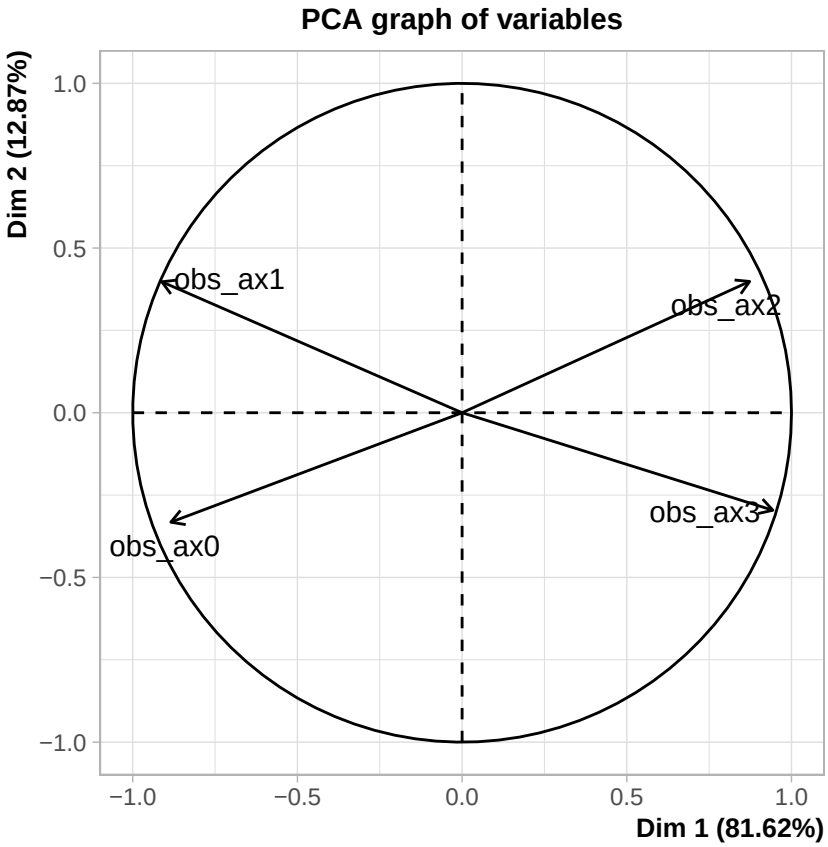



```
# PCA Variable Factor Map
# NOTE: scaling has no effect on fit
data_factor$act = states$act
res <- PCA(data_factor)
```

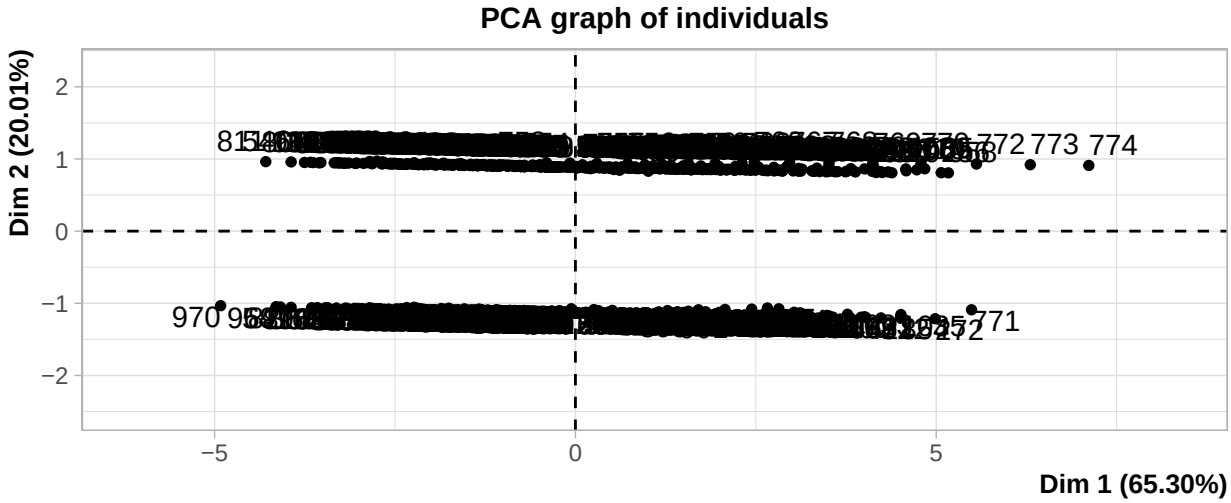


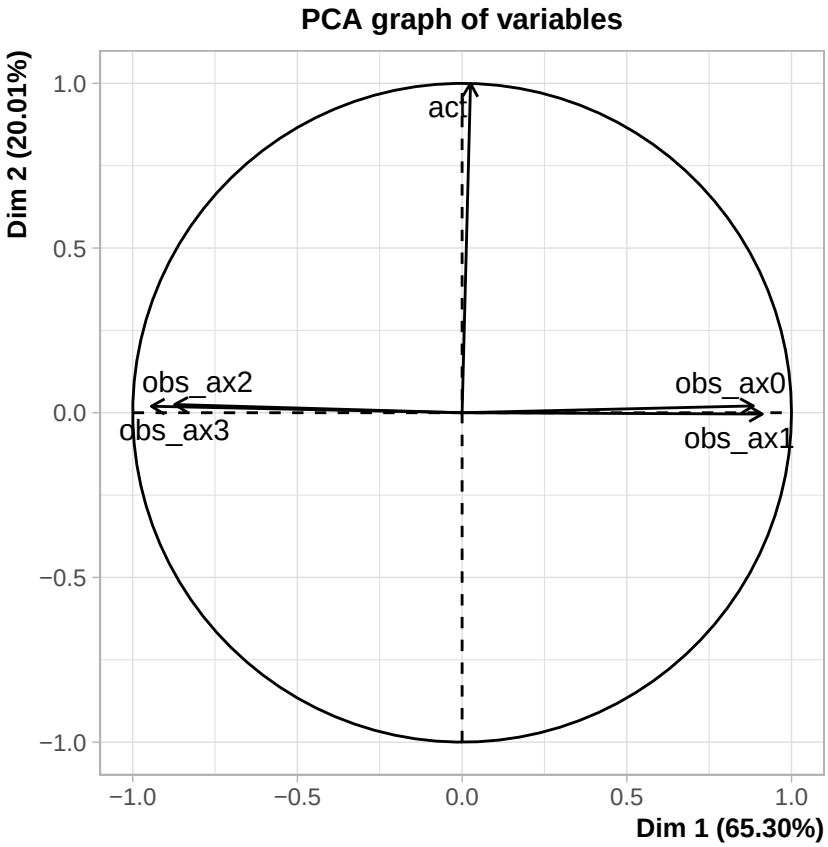

```
result <- PCA(mydata) # graphs generated automatically
```






```
result <- PCA(states) # graphs generated automatically
```




PCA graph of variables
Dim 2 (20.01%)
1.0
0.5
0.0
−0.5
−1.0
act
obs_ax2
obs_ax3
obs_ax0
obs_ax1
−1.0
−0.5
0.0
0.5
1.0
Dim 1 (65.30%)