Predict States

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```
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)
```

```
rand_state_acts <- read_csv("../utils/rand_state_acts.csv")
```

```
## Rows: 1047 Columns: 12
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (12): timestep, episode, reward, act, obs_ax0, next_ax0, obs_ax1, next_a...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
names(rand_state_acts)
```

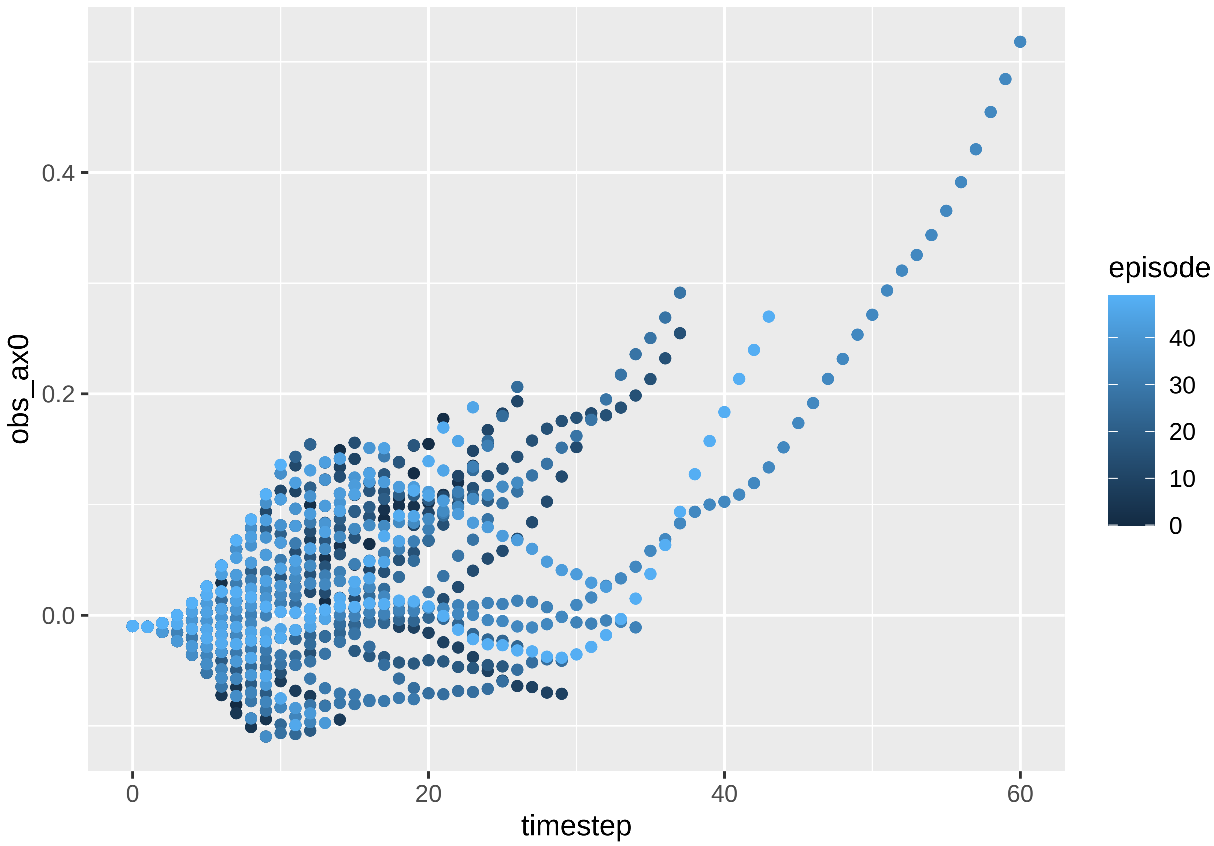
```
##  [1] "timestep" "episode"  "reward"   "act"      "obs_ax0"  "next_ax0"
##  [7] "obs_ax1"  "next_ax1" "obs_ax2"  "next_ax2" "obs_ax3"  "next_ax3"
```

```
# Roughly 50% of actions should be left
summary(rand_state_acts$act)
```

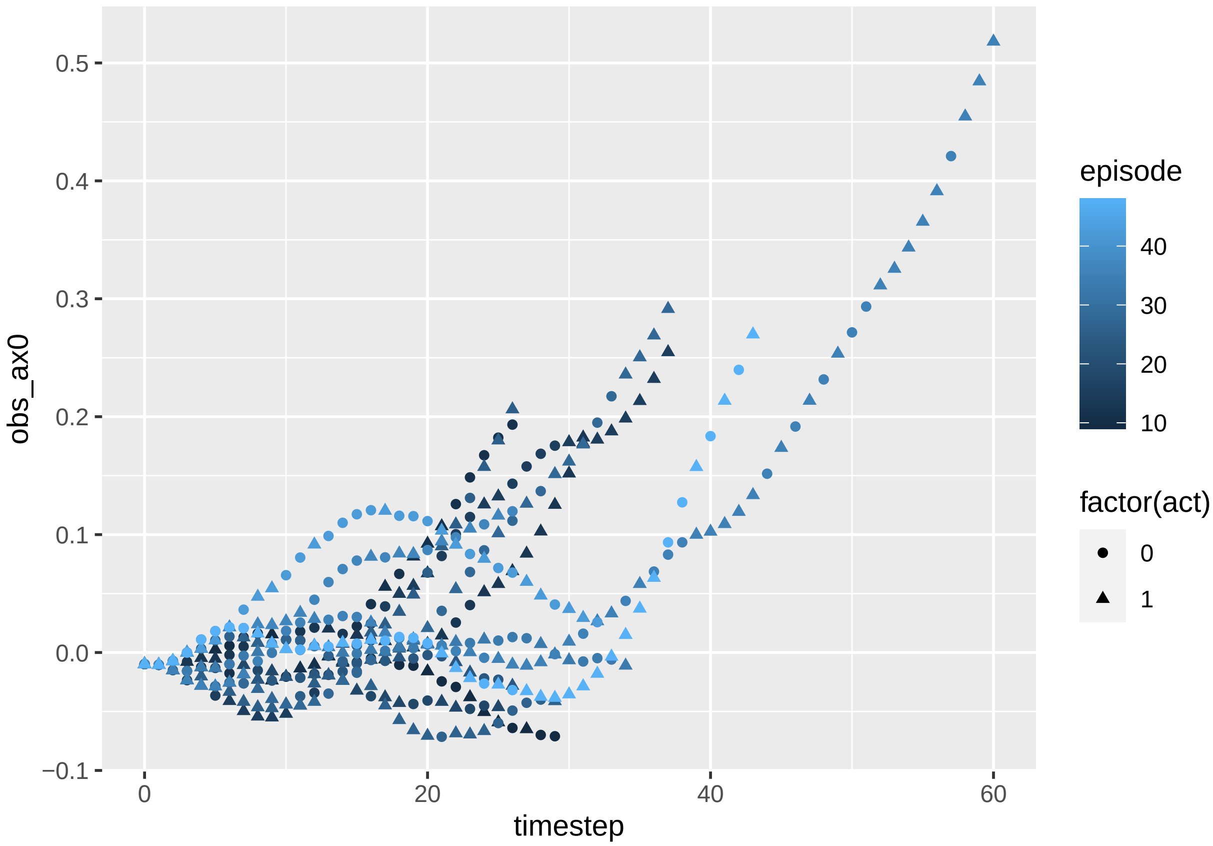
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  1.0000  0.5568  1.0000  1.0000
```

```
#pairs(rand_state_acts[5:12])
```

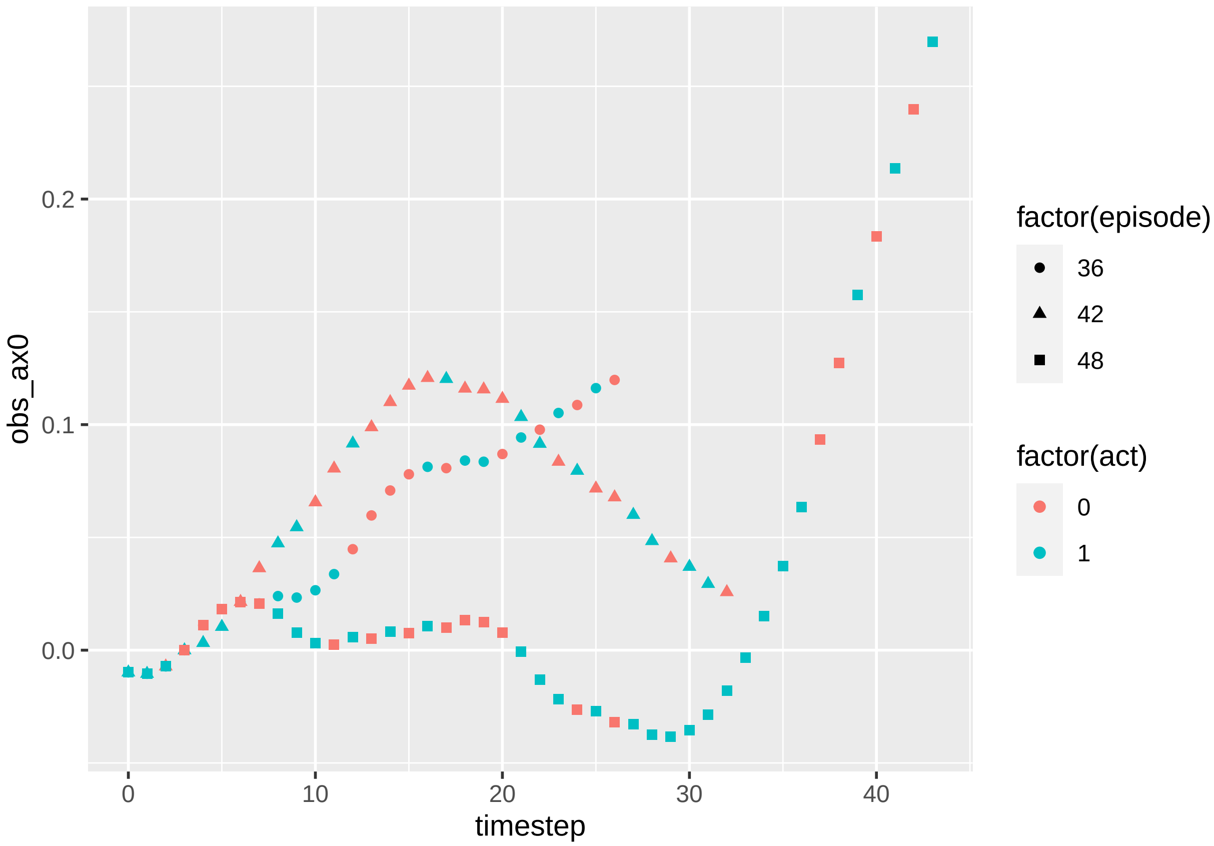
```
ggplot(rand_state_acts, aes(x=timestep, y=obs_ax0)) +
  geom_point(aes(colour=episode))
```




```
ggplot(filter(rand_state_acts, reward>mean(reward)),
  aes(x=timestep, y=obs_ax0, colour=episode, shape=factor(act))) +
  geom_point()
```




```
ggplot(filter(rand_state_acts,
              reward>mean(reward) & episode>35),
  aes(x=timestep, y=obs_ax0,
      shape=factor(episode),
      colour=factor(act))) +
  geom_point()
```




```
#binaxis = "x", binwidth = .01
```

```
ax0_pred = lm(obs_ax0 ~ next_ax0 + factor(act), data=rand_state_acts)
#summary(ax0_pred)

ax1_pred = lm(obs_ax1 ~ next_ax1 + factor(act), data=rand_state_acts)
summary(ax1_pred) # Act is a significant predictor here
```

```
##
## Call:
## lm(formula = obs_ax1 ~ next_ax1 + factor(act), data = rand_state_acts)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0037869 -0.0003614  0.0000835  0.0004948  0.0026689
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.953e-01  4.637e-05    4211   <2e-16 ***
## next_ax1       9.987e-01  5.793e-05   17242   <2e-16 ***
## factor(act)1 -3.895e-01  6.653e-05   -5854   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0009986 on 1044 degrees of freedom
## Multiple R-squared:      1,  Adjusted R-squared:      1
## F-statistic: 1.487e+08 on 2 and 1044 DF,  p-value: < 2.2e-16
```

```r
ax2_pred = lm(obs_ax2 ~ next_ax2 + factor(act), data=rand_state_acts)
#summary(ax2_pred)

ax3_pred = lm(obs_ax3 ~ next_ax3 + factor(act), data=rand_state_acts)
summary(ax3_pred) # Act is a significant predictor here
```

```
##
## Call:
## lm(formula = obs_ax3 ~ next_ax3 + factor(act), data = rand_state_acts)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.047750 -0.011018 -0.001487  0.008131  0.070536
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.2940545  0.0008783  -334.8   <2e-16 ***
## next_ax3      0.9732805  0.0007158  1359.7   <2e-16 ***
## factor(act)1  0.5665373  0.0012500   453.2   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01889 on 1044 degrees of freedom
## Multiple R-squared:  0.9994, Adjusted R-squared:  0.9994
## F-statistic: 9.244e+05 on 2 and 1044 DF,  p-value: < 2.2e-16
```

```r
states = data.frame(ax0=rand_state_acts$obs_ax0,
                    ax1=rand_state_acts$obs_ax1,
                    ax2=rand_state_acts$obs_ax2,
                    ax3=rand_state_acts$obs_ax3)
s_next = data.frame(ax0=rand_state_acts$next_ax0,
                    ax1=rand_state_acts$next_ax1,
                    ax2=rand_state_acts$next_ax2,
                    ax3=rand_state_acts$next_ax3)
```