Exposure Consequences - Statistics and Figures

1 Overview

Here I collect the 'right' statistics and figures for the exposure consequences project.

Here are the planned figures and tables:

Figures:

1. Setup & Task (goal: visualize the experiment)
   - A: Setup (side view)
   - B: Rotated training (top view)
   - C: No-cursor reaches (top view)
   - D: Localization (top view)
2. Reach Aftereffects (goal: show motor changes are there, are robust and compare to classic)
   - A: Exposure reach aftereffects (initial & later)
   - B: Classic & Exposure reach aftereffects (initial only? or all?)
3. Localization
   - A: Exposure, active and passive (goal: small/no difference between active and passive)
   - B: Classic, active and passive (goal: larger difference between active and passive, different generalization?)

Maybe:

4. Correlation
   - A: Exposure, active and passive localization predicting reach aftereffects
   - B: Classic, active and passive localization predicting reach aftereffects

Tables:

1. Task order & trial numbers (goal: clarify task order and show similarity between classic and exposure experiment - so probably after Fig 1)

1.1 Source scripts

All the scripts doing the statistics and figures are in separate R files, but here we will only see / do the ones that we think should go to the manuscript.

First we load those other scripts:

```
source('shared.R') # functions used everywhere
source('nocursor.R') # functions for no-cursor reach data
```

```
Loading required package: nlme
```

```
Loading required package: car
```

```
source('localization.R') # functions for localization data
source('relateLocalizationNoCursors.R') # functions that correlate the two kinds of data
```

1.2 Topics

In the manuscript we'll first show that there are motor changes after exposure training (with the no-cursor data) and then compare that with the classic. Second is the localization: a) localization shifts after exposure

b) the shifts are the same/different from those after classic c) the effects are different across the workspace d) this pattern is indistinguishable / different from that after classic. A third topic might be if localization shifts can predict no-cursor changes. Here we'll also follow this order:

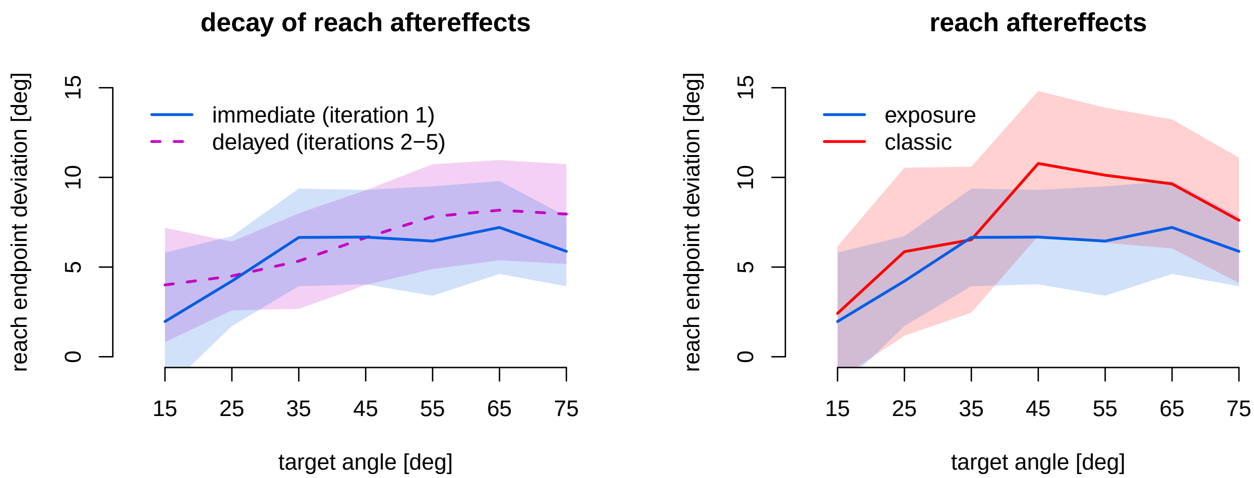
1. Reach aftereffects
2. Localization
3. Correlations

2 Reach Aftereffects

Here is a plot, probably Figure 2:

```
plotReachAftereffects()
```

```
removed 133 outliers, kept 96.6%
removed 131 outliers, kept 96.7%
removed 133 outliers, kept 96.6%
```



Messages of the figure:

- Panel A: there are substantial and persisting reach aftereffects
- Panel B: that are somewhat lower than those in classic (but not that much? but only for some targets?)

These claims require analyses.

2.1 Is there an effect of exposure training on reach aftereffects?

First, we show that no-cursor reaches change direction after exposure training:

```
exposureNoCursorChange()
```

```
removed 133 outliers, kept 96.6%

LME with session and target as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle
                 Chisq Df Pr(>Chisq)
(Intercept)     1.3733  1     0.2413
```

```
rotated        74.5681  1     <2e-16 ***
target          8.1406  6     0.2280
rotated:target  7.1149  6     0.3104
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

So this shows that whether or not the feedback was rotated mattered for the reach deviations in the exposure training group, i.e.: there are reach aftereffects.

2.2 Do the motor changes persist during localization?

The second analysis is to show that the reach aftereffects aren't all that different for first and later iterations of the rotated no-cursor tasks. (The baseline is always all aligned iterations of the task.)

```
exposureAftereffectsPersistent()
```

```
removed 133 outliers, kept 96.6%
removed 133 outliers, kept 96.6%

LME with session and target as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle
                  Chisq Df Pr(>Chisq)
(Intercept)      62.8173  1  2.268e-15 ***
iteration         1.6077  1  0.2048197
target           26.7191  6  0.0001634 ***
iteration:target  3.4796  6  0.7466863
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

So there is no effect of iteration here, which means the reach aftereffects are the same for the first iteration and the average across the other four iterations. We now also have enough power to see an effect of target angle (the generalization curve is not flat), but more importantly the effect of iteration is also not dependent on target.

2.3 Are reach aftereffects comparable between classic and exposure training?

Finally, we want to see if there is a difference between the reach aftereffects observed after exposure training and those after classic training.

```
exposureClassicReachAftereffects()
```

```
removed 133 outliers, kept 96.6%
removed 131 outliers, kept 96.7%

LME with training type and target as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle
                 Chisq Df Pr(>Chisq)
(Intercept)     56.1450  1  6.732e-14 ***
training         1.2828  1     0.2574
```

```
target          48.8245  6  8.084e-09 ***
training:target  5.4434  6     0.4883
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

I'd have expected there to be some difference between the two training types, perhaps only in interaction with target, but that's not the case apparently.

Let's minimize the potential explanatory power of the target by removing it from the model:

```
exposureClassicReachAftereffects(noTarget=TRUE)
```

```
removed 133 outliers, kept 96.6%
removed 131 outliers, kept 96.7%

LME with training type as fixed effects (without interacting), and participant and target as random effe

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle
              Chisq Df Pr(>Chisq)
(Intercept) 56.1450  1  6.732e-14 ***
training     1.2828  1     0.2574
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This doesn't seem to change anything, so that whether or not we account for any effects of target direction, there is no overall effect of training with volitional movements (classic) or passive movements (exposure) on – the amplitude of – reach aftereffects.

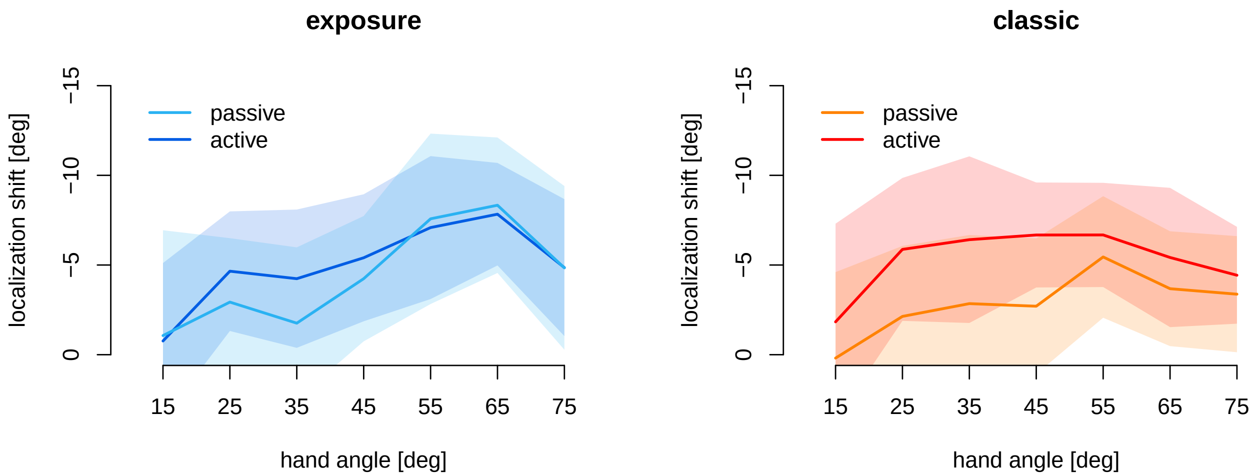
To sum up:

1. Rotated exposure training evokes substantial shifts in no-cursor reach direction,
2. these changes persist over time somewhat, and
3. these changes are comparable to the ones we found after classic training.

3 Localization

Here is a plot, probably figure 3:

```
plotLocalization()
```



That looks OK to me. It seems that just like after classic training, there is a change in localization responses following exposure training. There might still be a difference between active and passive localization after exposure training - contrary to our expectations - but it could be smaller than the difference after classic training. This will need to be tested.

3.1 Is there a localization shift after exposure training?

We first want to see if there is any overall effect of aligned versus rotated training in the exposure group, with movement type and hand angle as fixed effects, and particiant as random effect.

```
exposureLocalizationShift()
```

```
LME with session, target and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
                                  Chisq Df Pr(>Chisq)
(Intercept)                     20.4538  1  6.109e-06 ***
rotated_b                       97.2644  1  < 2.2e-16 ***
passive_b                        2.3744  1  0.1233378
handangle_deg                   27.7942  6  0.0001027 ***
rotated_b:passive_b              0.4726  1  0.4918084
rotated_b:handangle_deg         23.0677  6  0.0007741 ***
passive_b:handangle_deg          6.1902  6  0.4022226
rotated_b:passive_b:handangle_deg  1.3491  6  0.9688828
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Wether or not the feedback was rotated makes a difference according to two terms in the model. In other words: exposure training caused localization responses to shift (systematically), as we could already guess by looking at the figure.

This means we can look at the difference between repsonses after rotated and after aligned feedback: the training induced shift in localization.

3.2 Effects of movement type and hand angle in exposure localization

Let's first see if there is a difference between active and passive localization after exposure training.

```
exposureMovementType()
```

```
LME with hand angle and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
                         Chisq Df Pr(>Chisq)
(Intercept)             15.839  1  6.897e-05 ***
passive_b                0.458  1     0.4986
handangle_deg           30.480  6  3.185e-05 ***
passive_b:handangle_deg  2.182  6     0.9022
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It says there isn't, but let's make sure by not having hand angle in there as possibly stealing lots of variance.

```r
exposureMovementType(noHandAngle = TRUE)
```

```
LME with movement type as fixed effects - ignoring hand angle, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
              Chisq Df Pr(>Chisq)
(Intercept) 17.3415  1  3.123e-05 ***
passive_b    0.4269  1     0.5135
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

OK, so that is pretty clear: there is no difference between passive and active localization after exposure training, even with double the number of trials as in classic delayed.

3.3 Comparing localization after exposure and classic training

Now, let's see how this absence of a difference compares to that the (previously found difference) after classic training. Let's do this with an LME without all possible combinations of factors. We're primarily interested in the possibility that the effect of movement type is there after classic training, but not after exposure (that's our hypothesis). We're also somewhat interested in the effect of hand angle being different between classic and exposure training.

```r
exposureClassicLocalization(model='restricted')
```

```
LME with group, hand angle and movement type as fixed effects, and participant as random effect:
(BUT not with all combinations of terms in the model)

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
                      Chisq Df Pr(>Chisq)
(Intercept)         25.1282  1  5.364e-07 ***
group                0.1389  1  0.7093490
group:passive_b     14.4048  2  0.0007448 ***
group:handangle_deg 45.9050 12  7.205e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This works: the interaction between group and movement type indicates that the effect of movement is different for the exposure and for the classic groups. Since it wasn't there at all for the exposure group, this means that there should be an effect of movement type in the classic group, which is an easily testable hypothesis. We also see an interaction between group and hand angle, which would mean that the shape of the generalization curve is different for the two groups. This seems to also be visible in the data, but would be worth probing a little further.

However, we did this with a restricted model that only contained the terms of interest. Let's see if it is still there with a full model:

```r
exposureClassicLocalization(model='full')
```

```
LME with group, hand angle and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
                               Chisq Df Pr(>Chisq)
(Intercept)                  25.1298  1  5.360e-07 ***
group                         0.1406  1   0.707671
passive_b                     8.5880  1   0.003384 **
handangle_deg                37.9631  6  1.142e-06 ***
group:passive_b               3.6462  1   0.056198 .
group:handangle_deg           8.7167  6   0.190152
passive_b:handangle_deg       4.7792  6   0.572427
group:passive_b:handangle_deg 0.4043  6   0.998816
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Now it is only a trend, so let's follow this up with some deeper probing. In the restricted model there was also an interaction between group and hand angle which has all but vanished in the full model.

3.4 Effect of movement type after classic training

We already saw that in the exposure group there was an effect of hand angle, but not of movement type. How is this in the classic group?

```r
classicMovementType()
```

```
LME with hand angle and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
                          Chisq Df Pr(>Chisq)
(Intercept)             10.5466  1  0.0011640 **
passive_b               13.4464  1  0.0002455 ***
handangle_deg           13.8591  6  0.0312499 *
passive_b:handangle_deg  3.0647  6  0.8006839
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
classicMovementType(factors='movementtype')
```

```
LME with movement type as fixed effects - ignoring hand angle, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
             Chisq Df Pr(>Chisq)
(Intercept) 11.416  1  0.0007281 ***
passive_b   13.970  1  0.0001857 ***
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Alright, so there is an effect of movement type here as well as of hand angle. Since the exposure group saw no effect of movement type in either analysis, whereas there is an effect of movement type in the classic group in both analyses, we can be fairly confident that if there is any effect of movement type after exposure training it will be smaller than after classic training. This is what we would expect from exposure training.

3.5 Hand angle in classic training

We're still not too sure about the effect of hand angle though. In the figures the localization shift for the classic groups *appears* more homogeneous across the workspace as compared to the exposure group, but is that a real effect?

I'm not sure how to focus an analysis on that question, better than already done, except by using a model with only hand angle:

```r
classicMovementType(factors='handangle')
```

```
LME with movement type as fixed effects - ignoring hand angle, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
               Chisq Df Pr(>Chisq)
(Intercept)   10.649  1   0.001102 **
handangle_deg 13.271  6   0.038926 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

So yes, there is some generalization effect after classic training. We still want to know if it is different from the effect of hand angle in exposure.

```r
exposureClassicLocalization(model='handangle')
```

```
LME with group, hand angle and movement type as fixed effects, and participant as random effect:
(BUT not with all combinations of terms in the model)

Analysis of Deviance Table (Type III tests)

Response: taperror_deg
                      Chisq Df Pr(>Chisq)
(Intercept)         25.2481  1  5.041e-07 ***
group                0.1349  1     0.7135
handangle_deg       37.5798  6  1.357e-06 ***
group:handangle_deg  8.6200  6     0.1961
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

According to all these analyses, the generalization is not appreciably different between classic and exposure training.

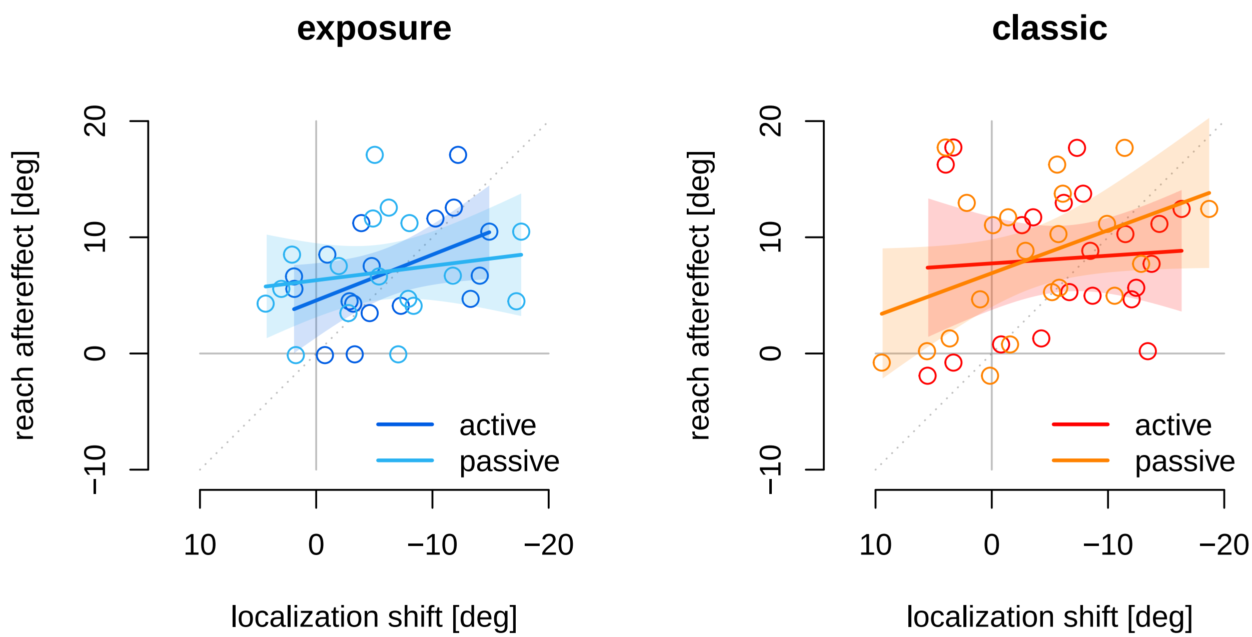
4 Correlation

In this section we look at how recalibrated proprioception (hand localization) correlates with reach aftereffects.

This plot shows regression lines with localization shifts as predictor of reach aftereffects:

```
correlations <- correlateNoCursorsLocalization()
```

```
removed 133 outliers, kept 96.6%
removed 131 outliers, kept 96.7%
```



It looks like for exposure, active localization is the better predictor of reach aftereffects, whereas in classic it is passive localization. But are any of them real?

4.1 Correlations

As one possibility, we can look at the correlations. Not just the p-values, but there are confidence intervals for Pearson's ρ, which allow to directly see if one correlation is stronger/weaker than another:

```
for (name in names(correlations)) {
  cat(name)
  print(correlations[[name]][['cortest']])
}
```

```
EXPOSURE ACTIVE

    Pearson's product-moment correlation

data:  X and Y
t = -2.1481, df = 15, p-value = 0.04845
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.783108393 -0.005712963
sample estimates:
       cor
```

```
-0.4850259

EXPOSURE PASSIVE

    Pearson's product-moment correlation

data:  X and Y
t = -0.68491, df = 15, p-value = 0.5038
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.6042126  0.3345023
sample estimates:
       cor
-0.1741402

CLASSIC ACTIVE

    Pearson's product-moment correlation

data:  X and Y
t = -0.31524, df = 19, p-value = 0.756
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4886046  0.3711104
sample estimates:
        cor
-0.07213219

CLASSIC PASSIVE

    Pearson's product-moment correlation

data:  X and Y
t = -1.9954, df = 19, p-value = 0.06054
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.71877161  0.01883464
sample estimates:
       cor
-0.4162364
```

And those linear regression models?

```r
for (name in names(correlations)) {
  cat(name)
  print(correlations[[name]][['linearm']])
}
```

```
EXPOSURE ACTIVE

Call:
lm(formula = Y ~ X)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-5.9446 -3.3323  0.0546  3.0104  7.7209

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.5660     1.5022   3.040  0.00828 **
X            -0.3939     0.1834  -2.148  0.04845 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.1 on 15 degrees of freedom
Multiple R-squared:  0.2353,    Adjusted R-squared:  0.1843
F-statistic: 4.614 on 1 and 15 DF,  p-value: 0.04845

EXPOSURE PASSIVE

Call:
lm(formula = Y ~ X)

Residuals:
    Min      1Q  Median      3Q     Max
-7.2549 -3.1740 -0.3723  2.4629 10.1650

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.3043     1.4969   4.212 0.000755 ***
X            -0.1243     0.1814  -0.685 0.503850
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.617 on 15 degrees of freedom
Multiple R-squared:  0.03032,   Adjusted R-squared:  -0.03432
F-statistic: 0.4691 on 1 and 15 DF,  p-value: 0.5038

CLASSIC ACTIVE

Call:
lm(formula = Y ~ X)

Residuals:
   Min     1Q Median     3Q    Max
-9.300 -3.891  0.519  3.733 10.196

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.75226    1.91381   4.051 0.000682 ***
X           -0.06652    0.21103  -0.315 0.756017
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.222 on 19 degrees of freedom
Multiple R-squared:  0.005203,  Adjusted R-squared:  -0.04715
F-statistic: 0.09938 on 1 and 19 DF,  p-value: 0.756

CLASSIC PASSIVE
```

```
Call:
lm(formula = Y ~ X)

Residuals:
   Min     1Q Median     3Q    Max
-8.771 -4.200 -1.377  4.290 12.280

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.9115     1.3909   4.969 8.52e-05 ***
X            -0.3693     0.1851  -1.995   0.0605 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.672 on 19 degrees of freedom
Multiple R-squared:  0.1733,    Adjusted R-squared:  0.1297
F-statistic: 3.982 on 1 and 19 DF,  p-value: 0.06054
```

They get the same p-value, so that seems fine.