Modeling discrete time-series data from a driving simulator

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Main Questions

- Do drivers with Alzheimer's disease tend to drive worse than those without Alzheimer's?
- Do drivers perform better or worse with mental stimulus?

Secondary Questions

- Can we produce a simulation that resembles a person's driving patterns?

Data Collection

- Simulator for Interdisciplinary Research in Ergonomics and Neuroscience (SIREN), a driving simulator at the University of Iowa Department of Neurology
  - Two time periods (straight road)
    1. PASAT (60 second timed addition task): http://www.nationalmssociety.org/ms-clinical-care-network/researchers/clinical-study-measures/pasat/index.aspx
    2. No task, some conversation between driver and proctor (~2 minutes)

SIREN (Driving Simulator)

Here, a fellow ISIB participant Lesly A. gets a feel of driving in the simulator.

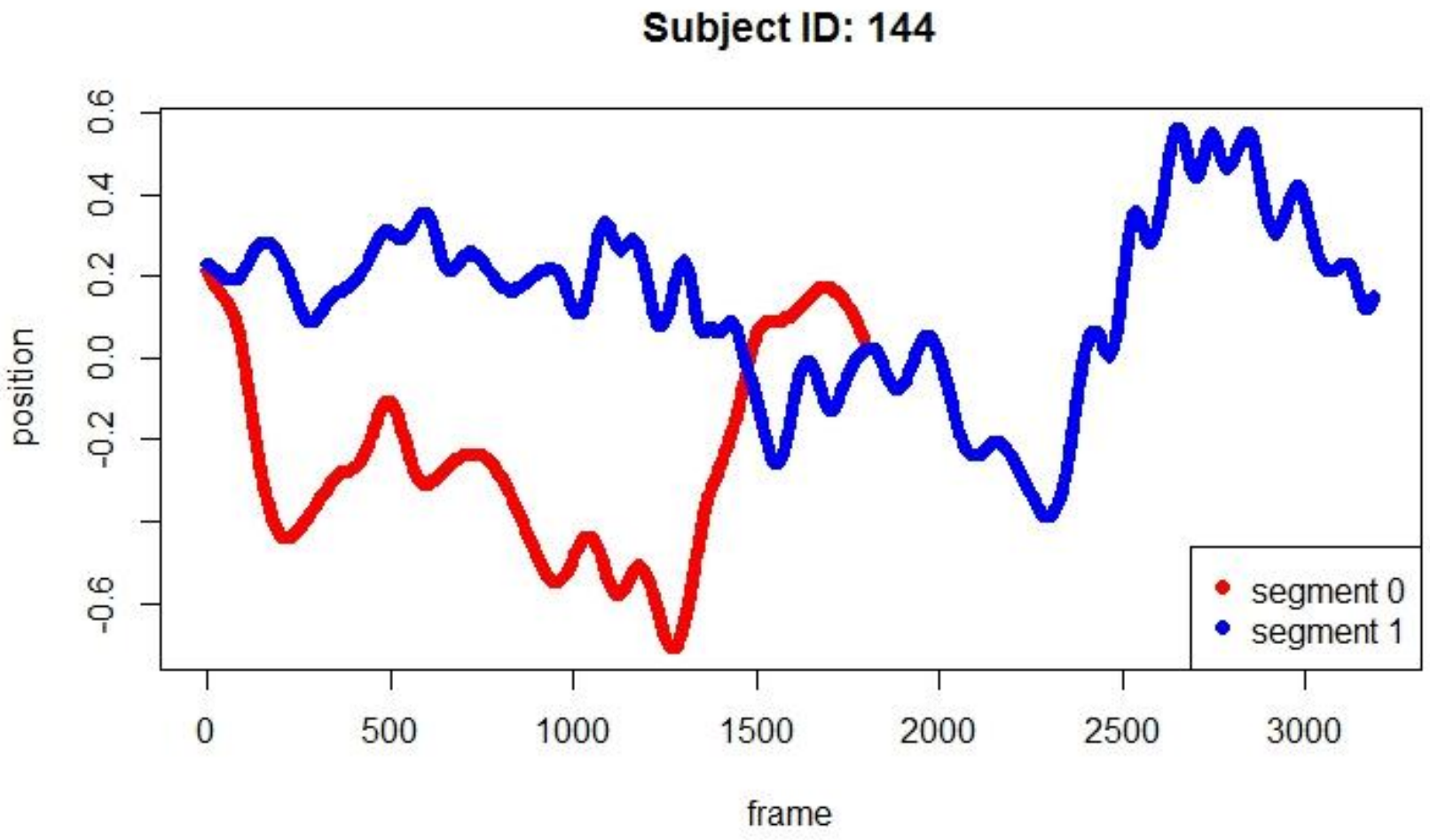
Data Collection, cont'd

- Participants

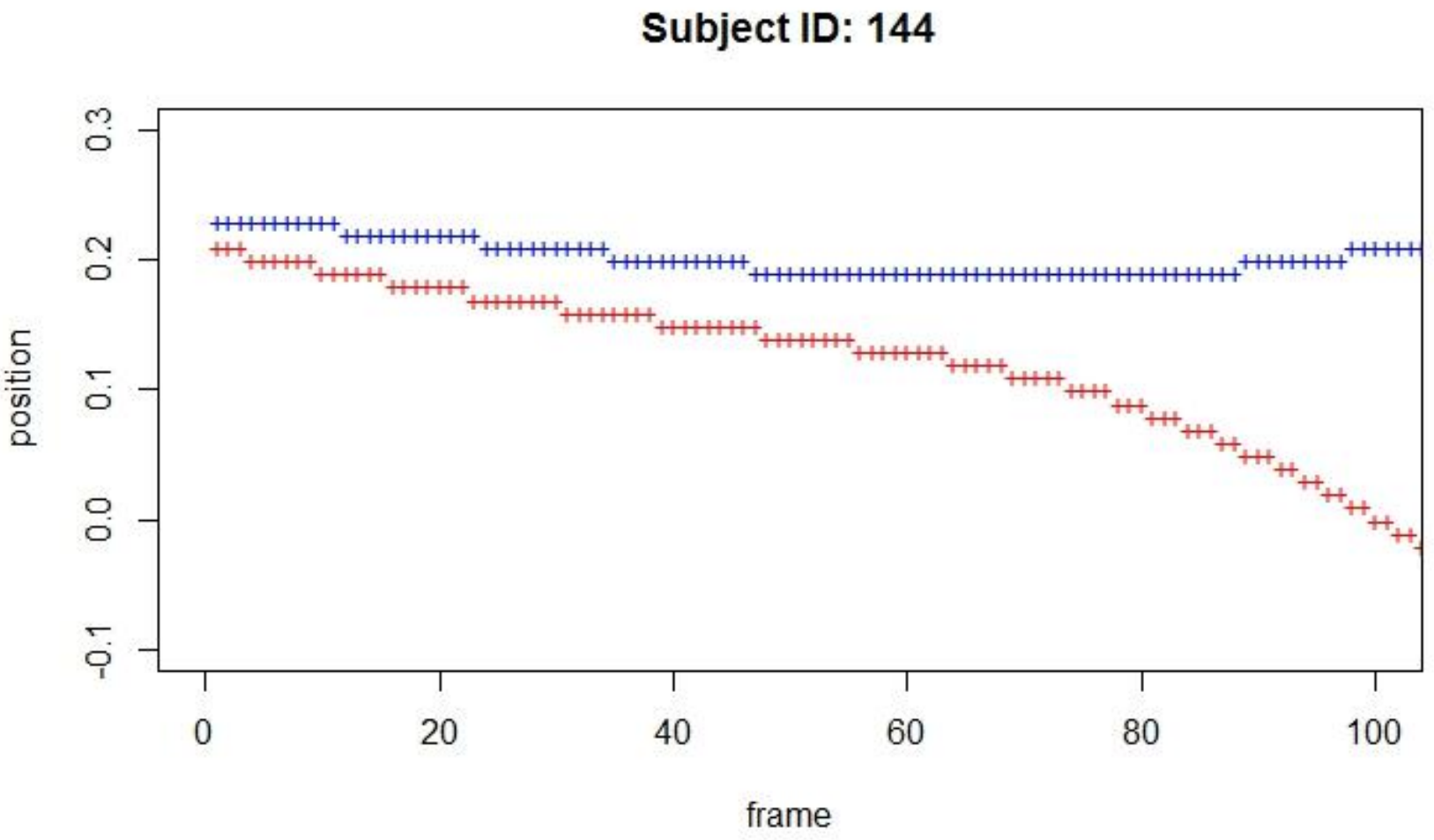
  Labeling:

  - Disease vs. no disease
    1. 69 with Alzheimer's disease (AD): numbered 1 to 69
    2. 130 control: numbered 70 to 199
  - Driving periods
    1. PASAT: segment 0 (1800 frames = 60 seconds)
    2. No task: segment 1 (~3000 to ~3800 frames ≈ 120 seconds)

Sample Data (subject 144)



Up-close look (not continuous)



Potential Problems with Data

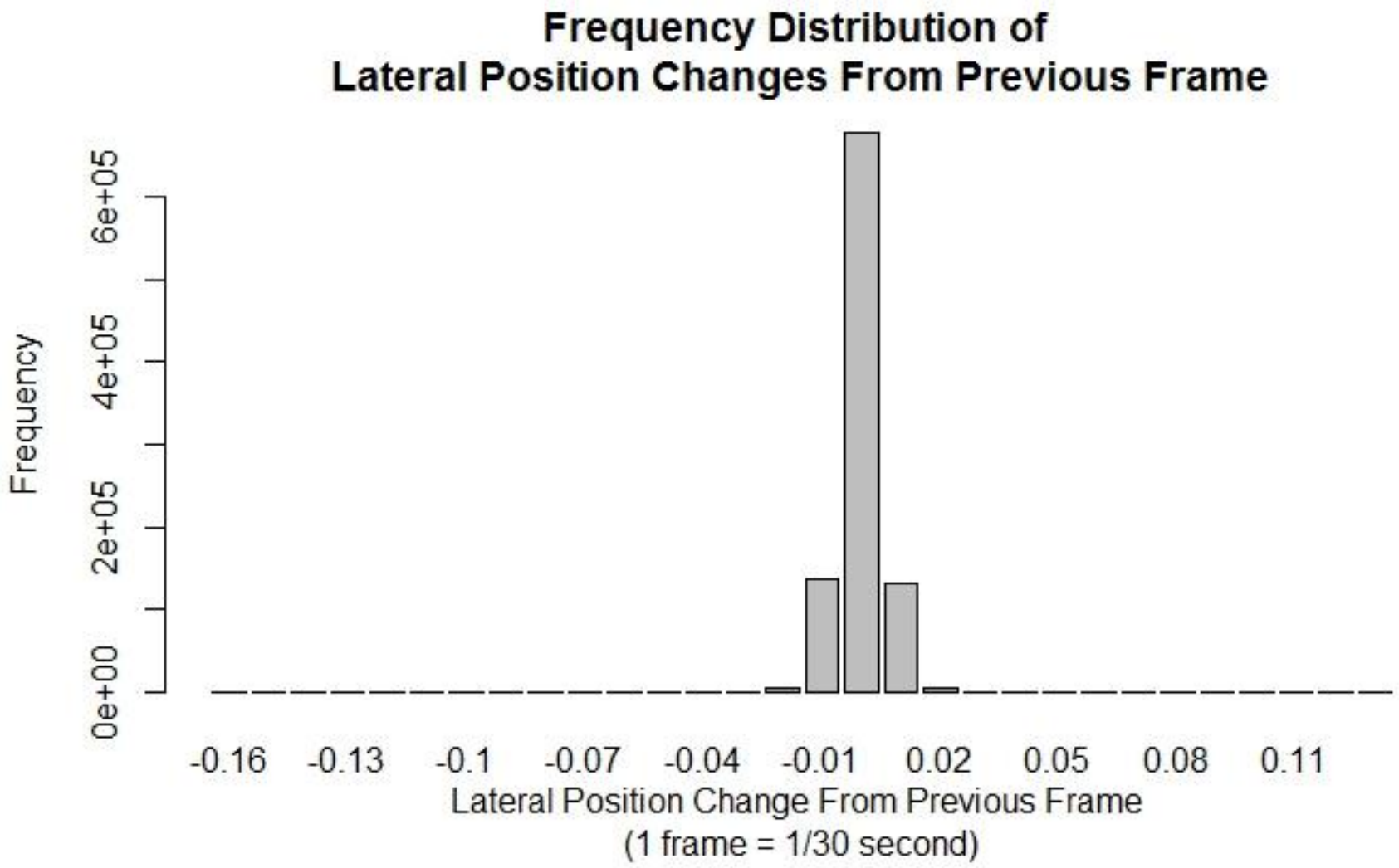
- Some participants only had one segments' data
- Precision is to two decimals which may obscure changing position in periods of no change
- Some major outliers in lateral position change when trivializing lateral position change into 3 categories shown later (move left, right, or not at all)

Analysis/Results

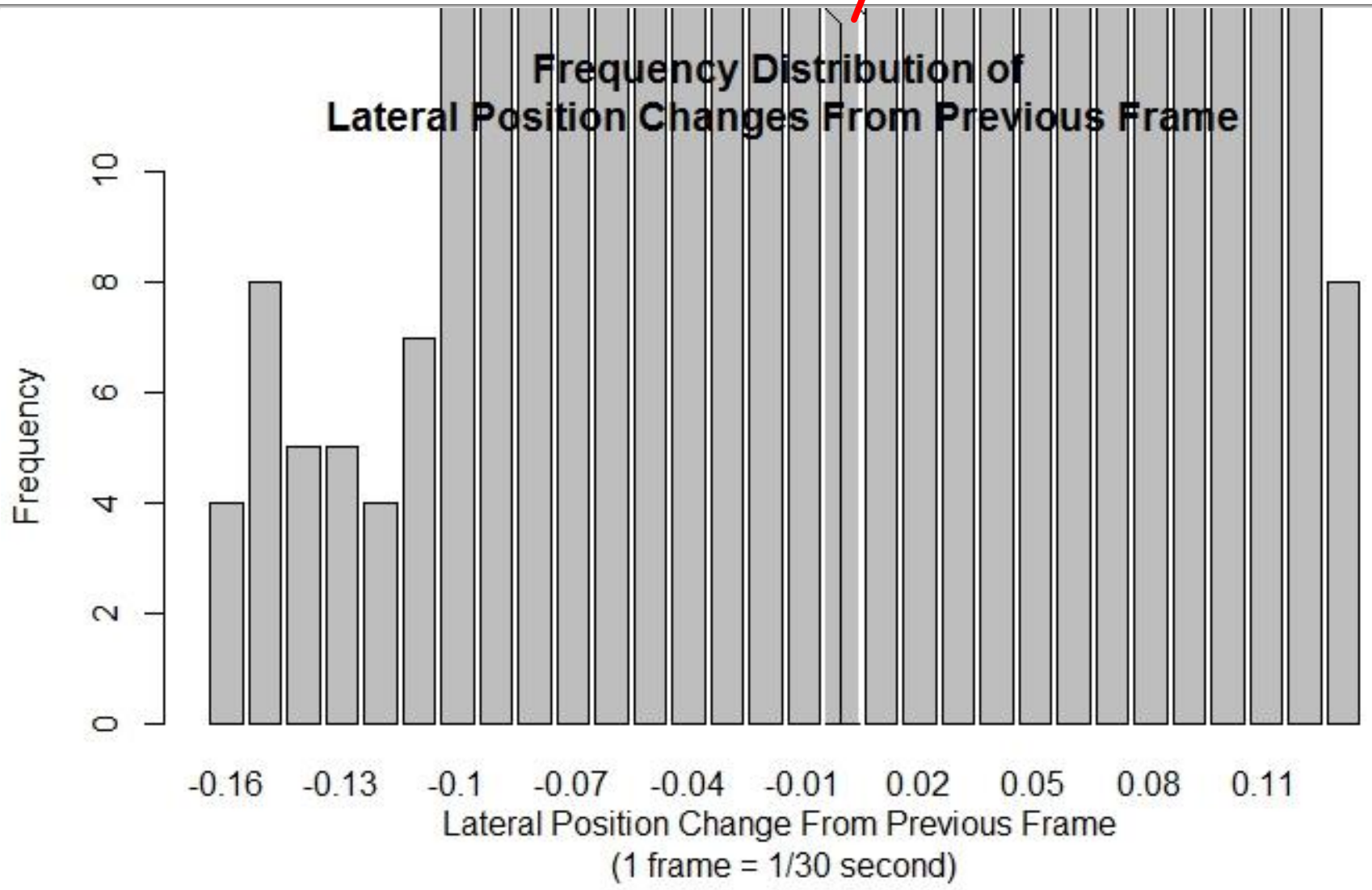
- Statistical software: R
- Ordinal Logistic Regression
  ("polr" function in R: proportional odds logistic regression)
  - Use lateral position/difference from previous lateral position to model probabilities of moving to the left, right or staying in the same place*

    *Consideration: some point-to-point lateral position differences had magnitude greater than .01, but this occurred in a very small percentage; distribution shown in a few slides)
  - Precision: 2 decimal places (hundredths)

- For the ordinal logistic regression model, we had three categorical variables: (-1, 0, and 1) which correspond to a change in lateral position to the left, no change, and to the right, respectively.
- Each of the variables (-1, 0, and 1) correspond to <0(left), 0, and >0(right) lateral position changes, respectively, and for modeling purposes, correspond to -0.01, 0, and 0.01 lateral position changes, respectively.
  - Only three categories are used to simplify the modeling process and because the frequency of other lateral position changes were negligible, illustrated in the following two slides:


Frequency Distribution of
Lateral Position Changes From Previous Frame
Frequency
0e+00
2e+05
4e+05
6e+05
-0.16
-0.13
-0.1
-0.07
-0.04
-0.01
0.02
0.05
0.08
0.11
Lateral Position Change From Previous Frame
(1 frame = 1/30 second)

This bent bar indicates that the height at 0.00 lateral position change is very high



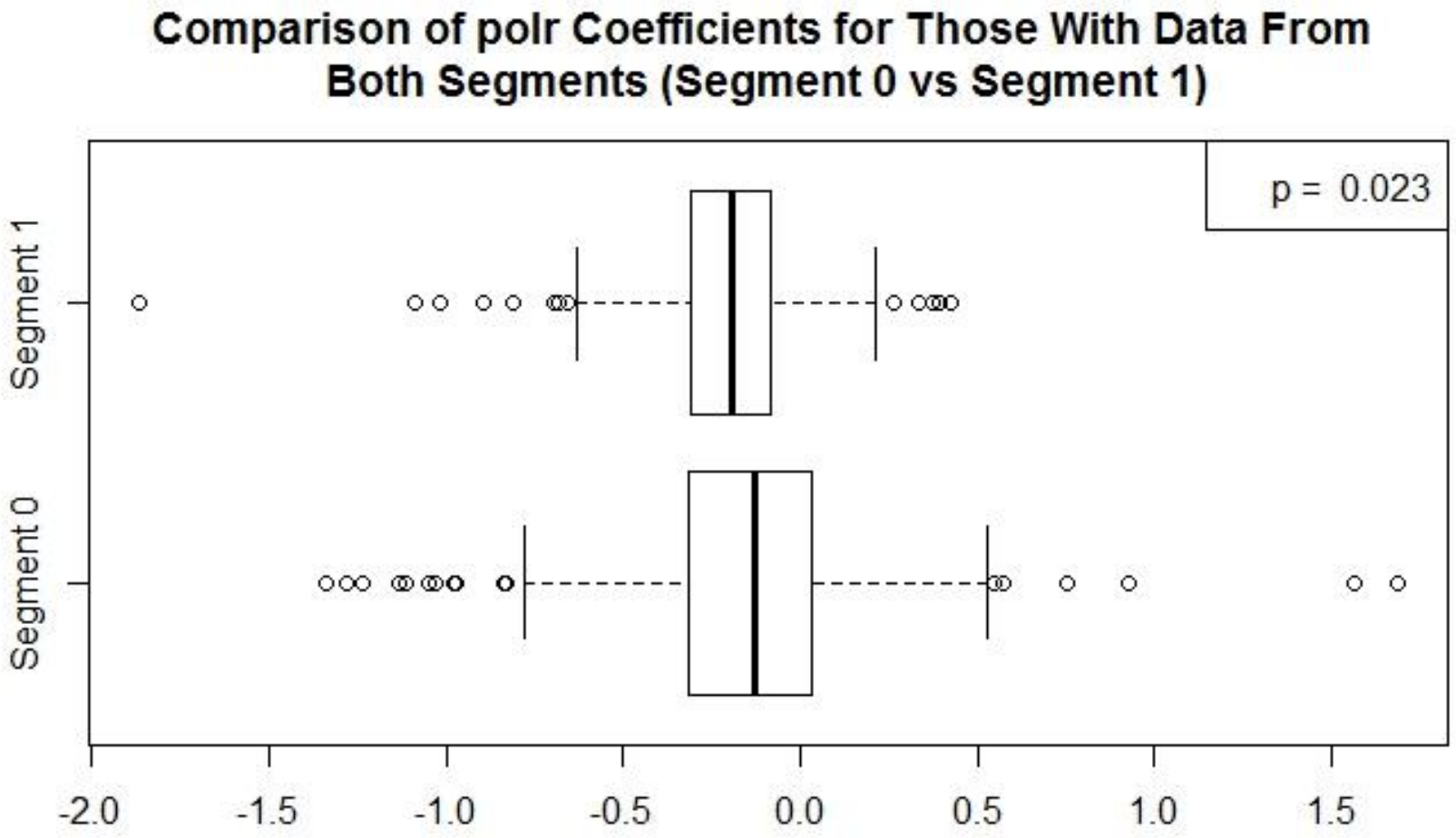
- t-tests
  - 2-sample Paired t-test of coefficients of the ordinal logistic regression model for those with both segments' data, segment 0 vs segment 1 (All, AD, control)
  - 2-sample t-test of coefficients of the ordinal logistic regression model for AD and control (segment 0 vs segment 1)

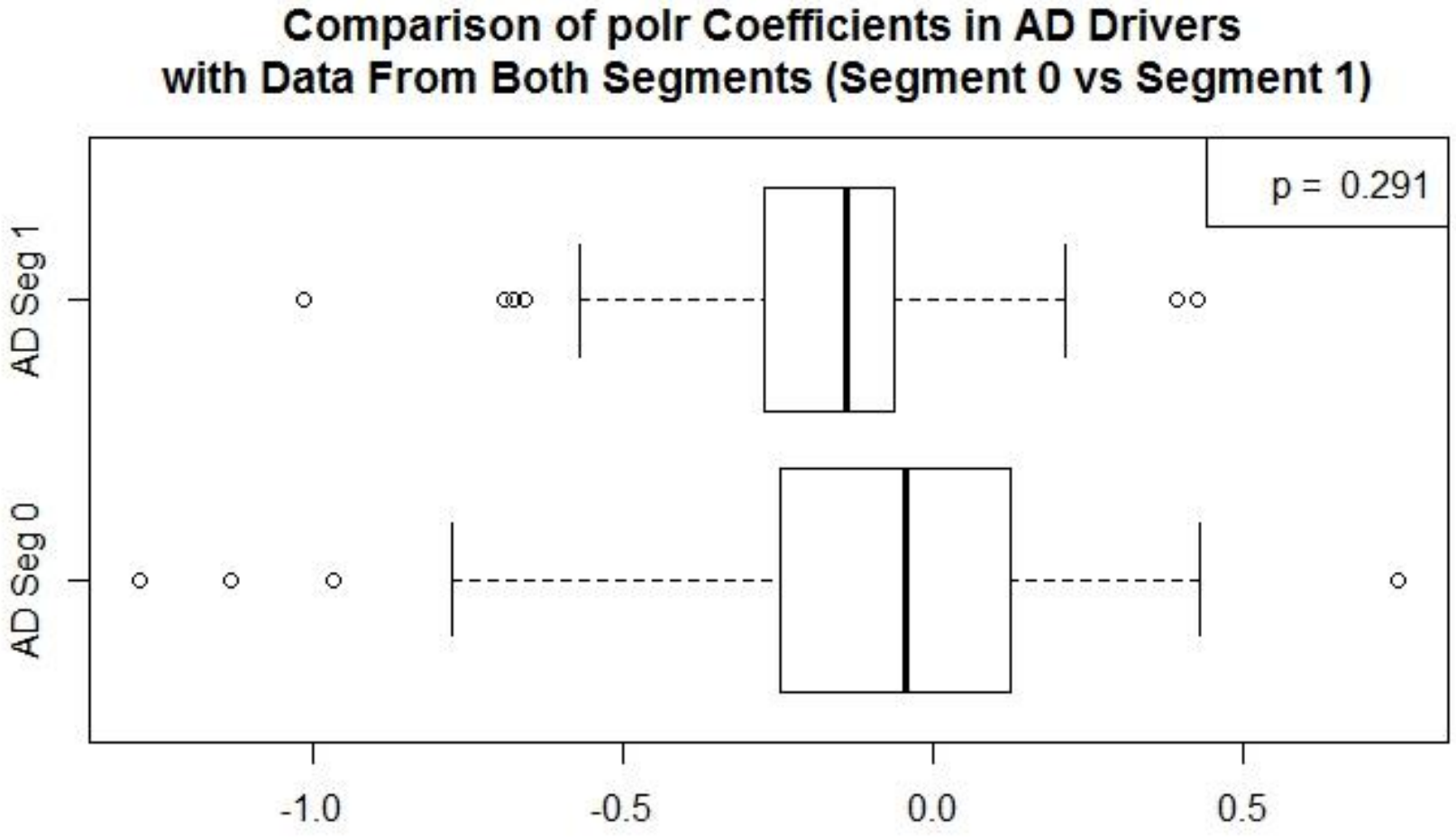
- For the coefficients of the ordinal logistic regression model, a negative coefficient indicates a negative-exponent curve around the center, which indicates an attempt to re-center the vehicle.

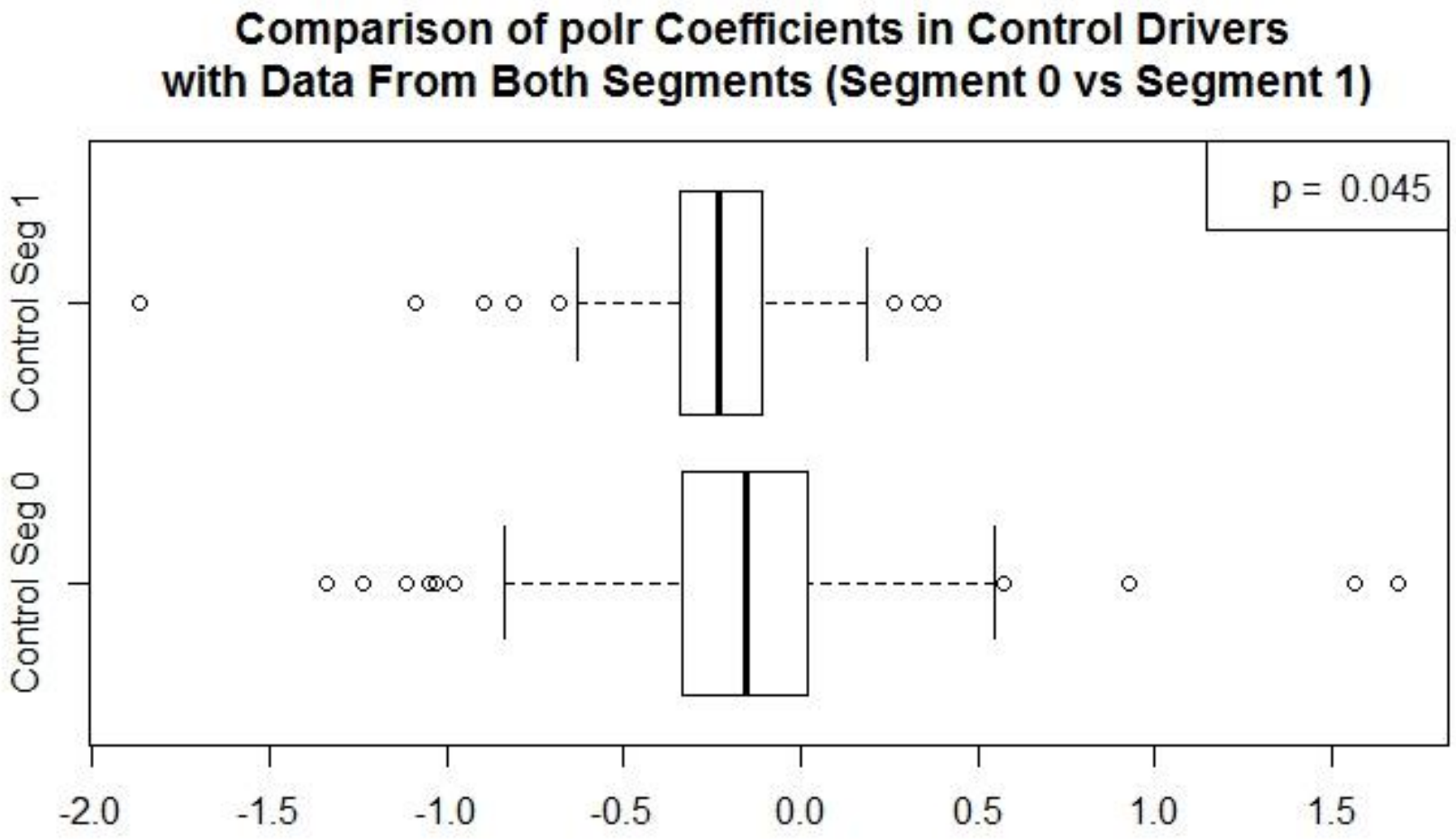
- A larger negative coefficient corresponds to a larger negative exponent, which means a greater re-centering effort.

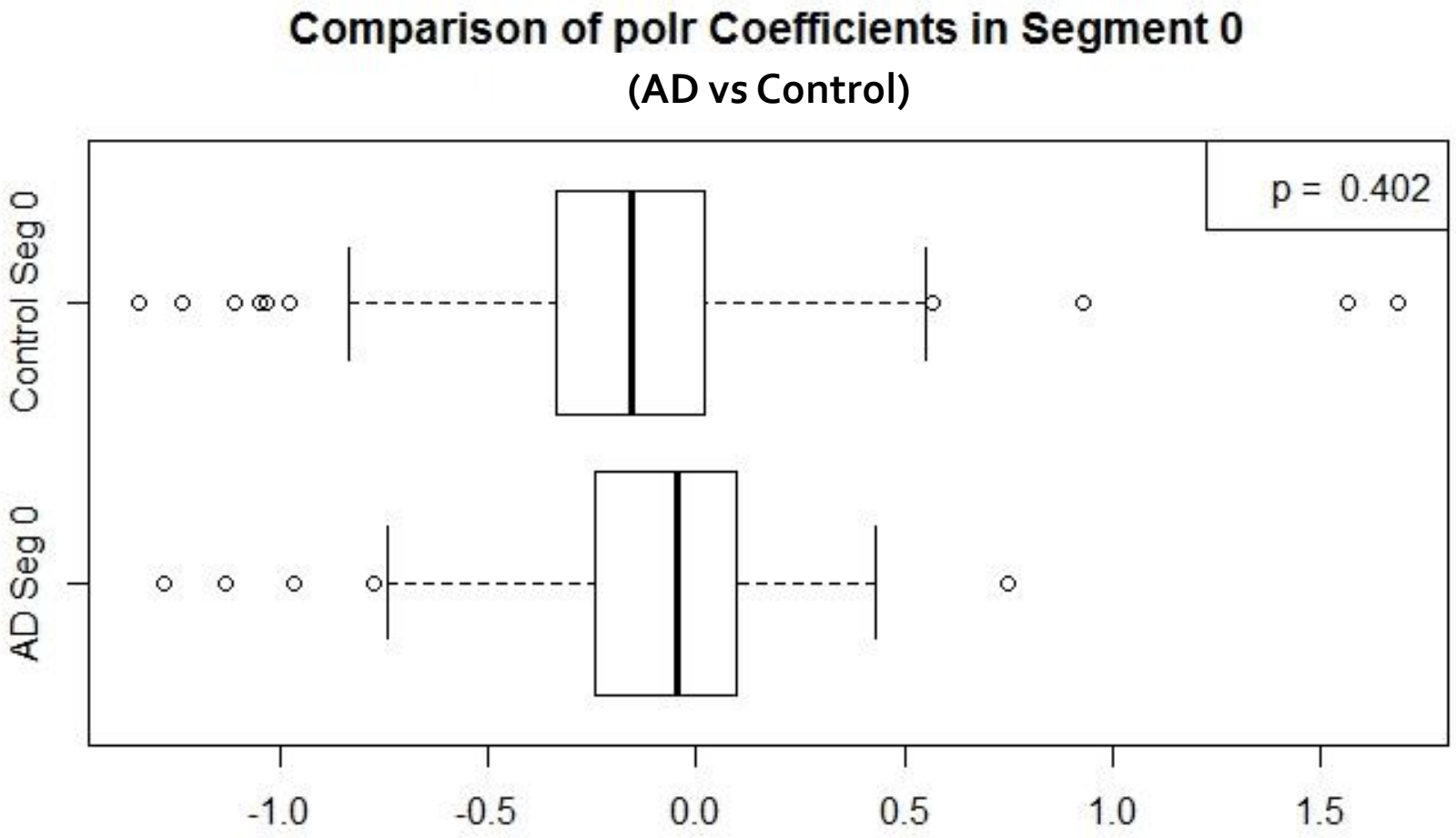
Following is a summary of the coefficients of our model:

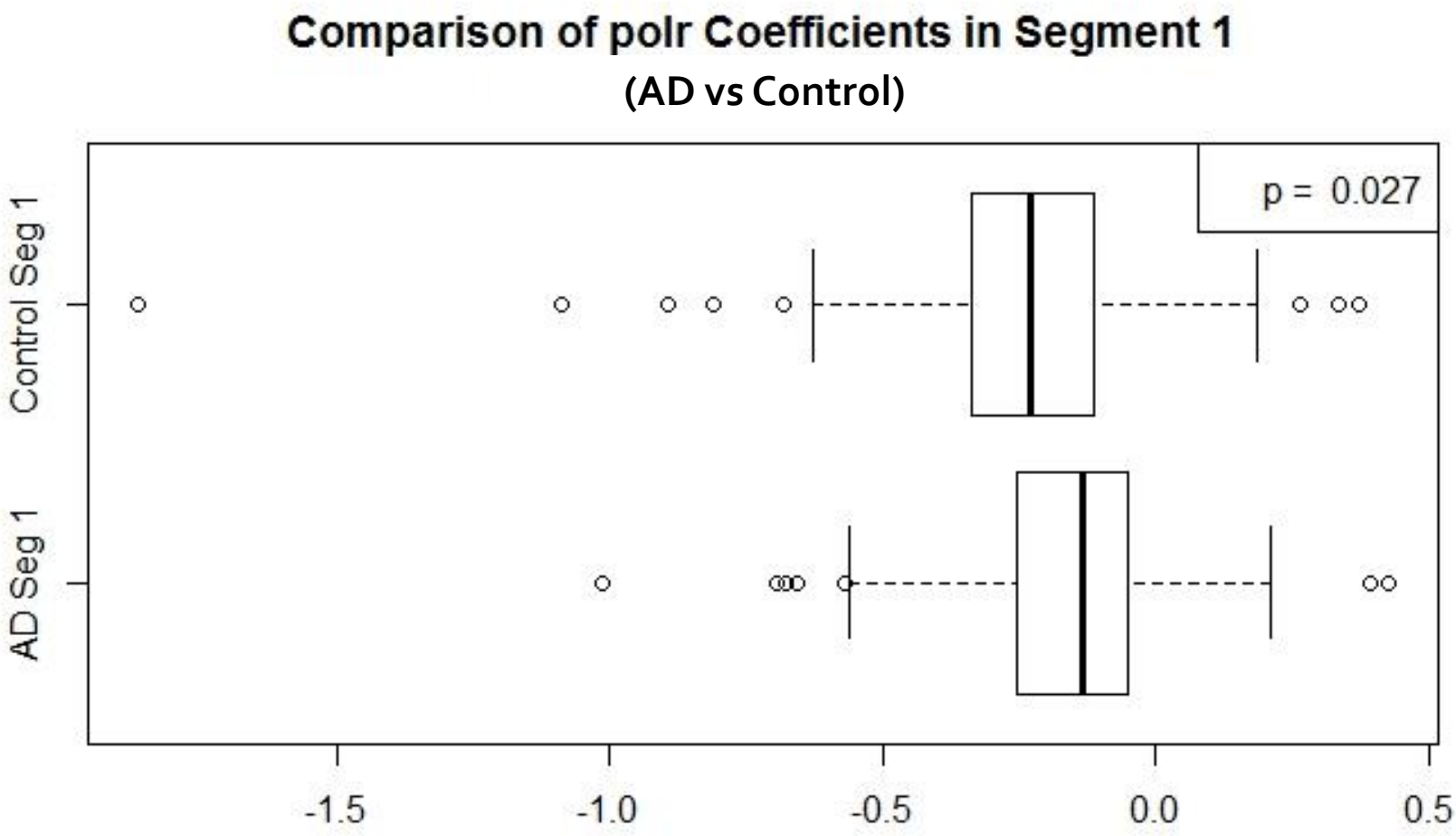
- Average coefficients (β)
  - Segment 0
    - Overall: -0.145
    - AD: -0.114
    - Control: -0.162
  - Segment 1
    - Overall: -0.219
    - AD: -0.163
    - Control: -0.247


Comparison of polr Coefficients for Those With Data From Both Segments (Segment 0 vs Segment 1)
p = 0.023
Segment 1
Segment 0
-2.0
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5

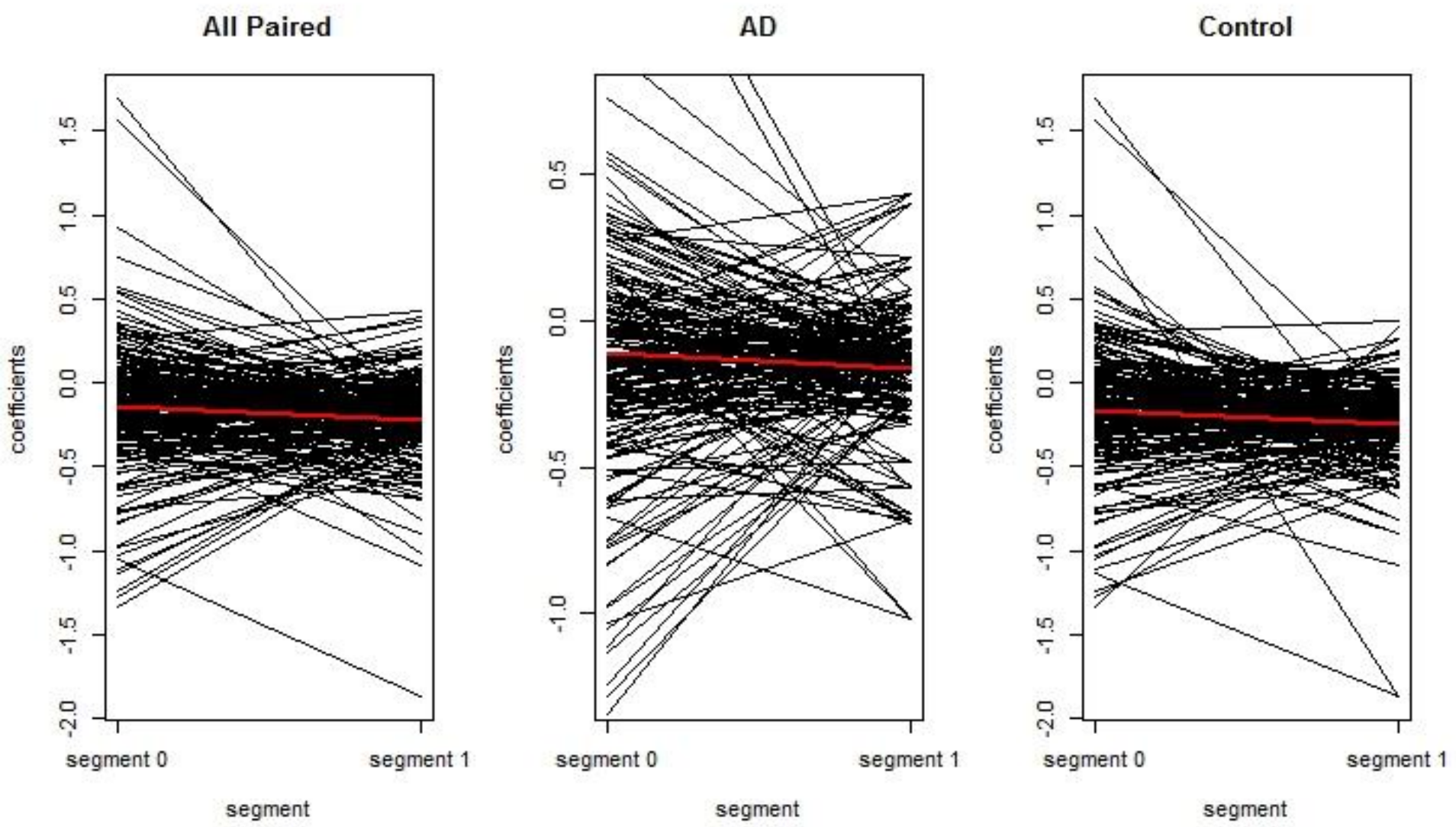

Comparison of polr Coefficients in AD Drivers
with Data From Both Segments (Segment 0 vs Segment 1)
p = 0.291
AD Seg 1
AD Seg 0
-1.0
-0.5
0.0
0.5


Comparison of polr Coefficients in Control Drivers
with Data From Both Segments (Segment 0 vs Segment 1)
p = 0.045
Control Seg 1
Control Seg 0
-2.0
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5


Comparison of polr Coefficients in Segment 0
(AD vs Control)
p = 0.402
Control Seg 0
AD Seg 0
-1.0
-0.5
0.0
0.5
1.0
1.5


Comparison of polr Coefficients in Segment 1
(AD vs Control)
p = 0.027
Control Seg 1
AD Seg 1
-1.5
-1.0
-0.5
0.0
0.5

Coefficient Comparison for People With Both Segments' Data



Do drivers with Alzheimer's disease tend to drive worse than those without Alzheimer's?

- For segment 0, we have a p-value of 0.402 when comparing AD to control, which is not statistically significant.
- For segment 1, we have a p-value of 0.027 when comparing AD to control, which is statistically significant.

Do drivers perform better or worse with mental stimulus?

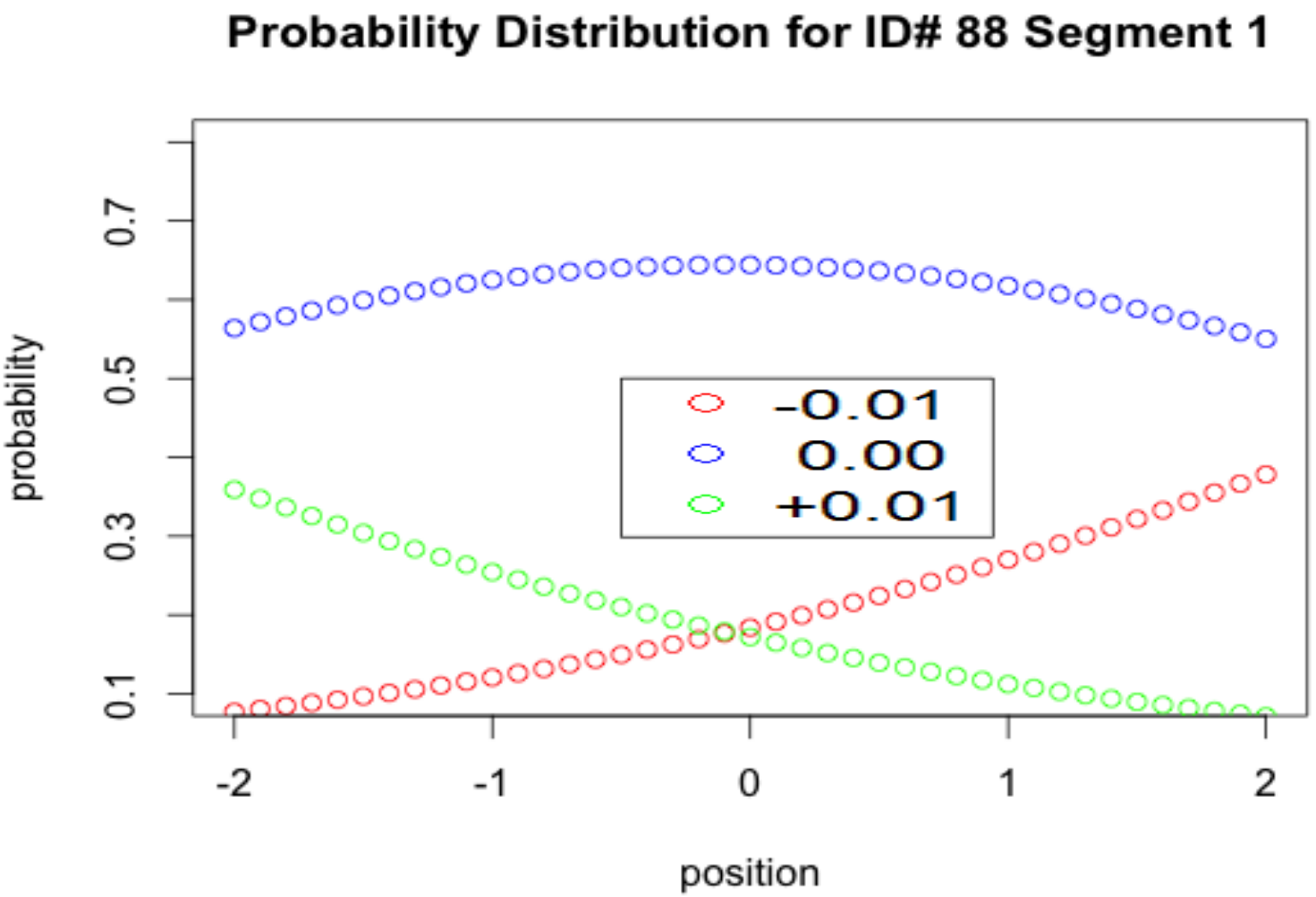
- Overall, participants did better during the PASAT (p-value 0.023)
- In the AD group, there was no strong evidence to support a difference in performance (p-value 0.291)
- In the control group, participants did better overall during the PASAT, but it is not strongly supported (p-value 0.045)

Can we produce a simulation that resembles a person's driving patterns?

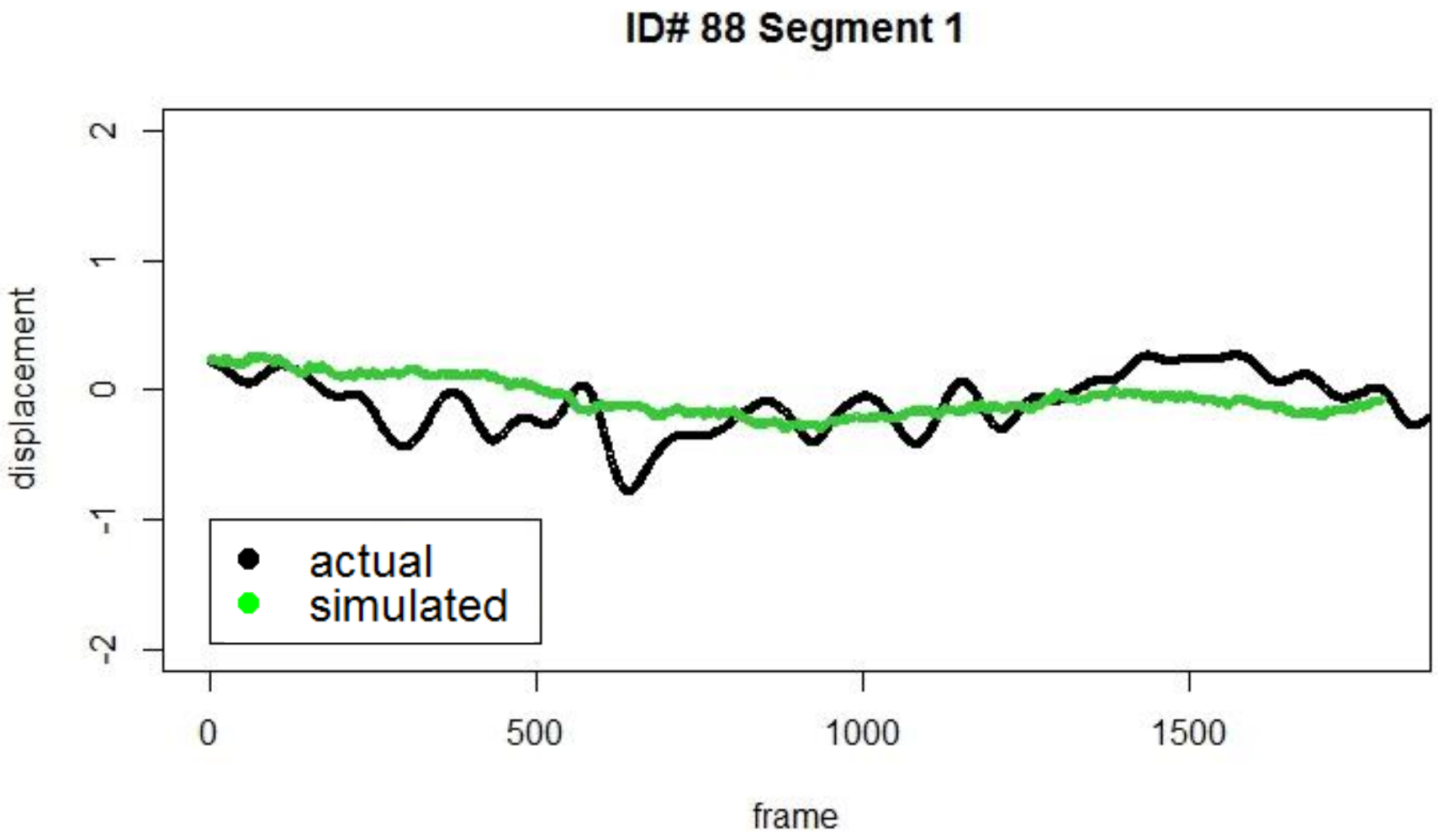
- We used the results of our ordinal logistic regression model to calculate movement probabilities for each participant

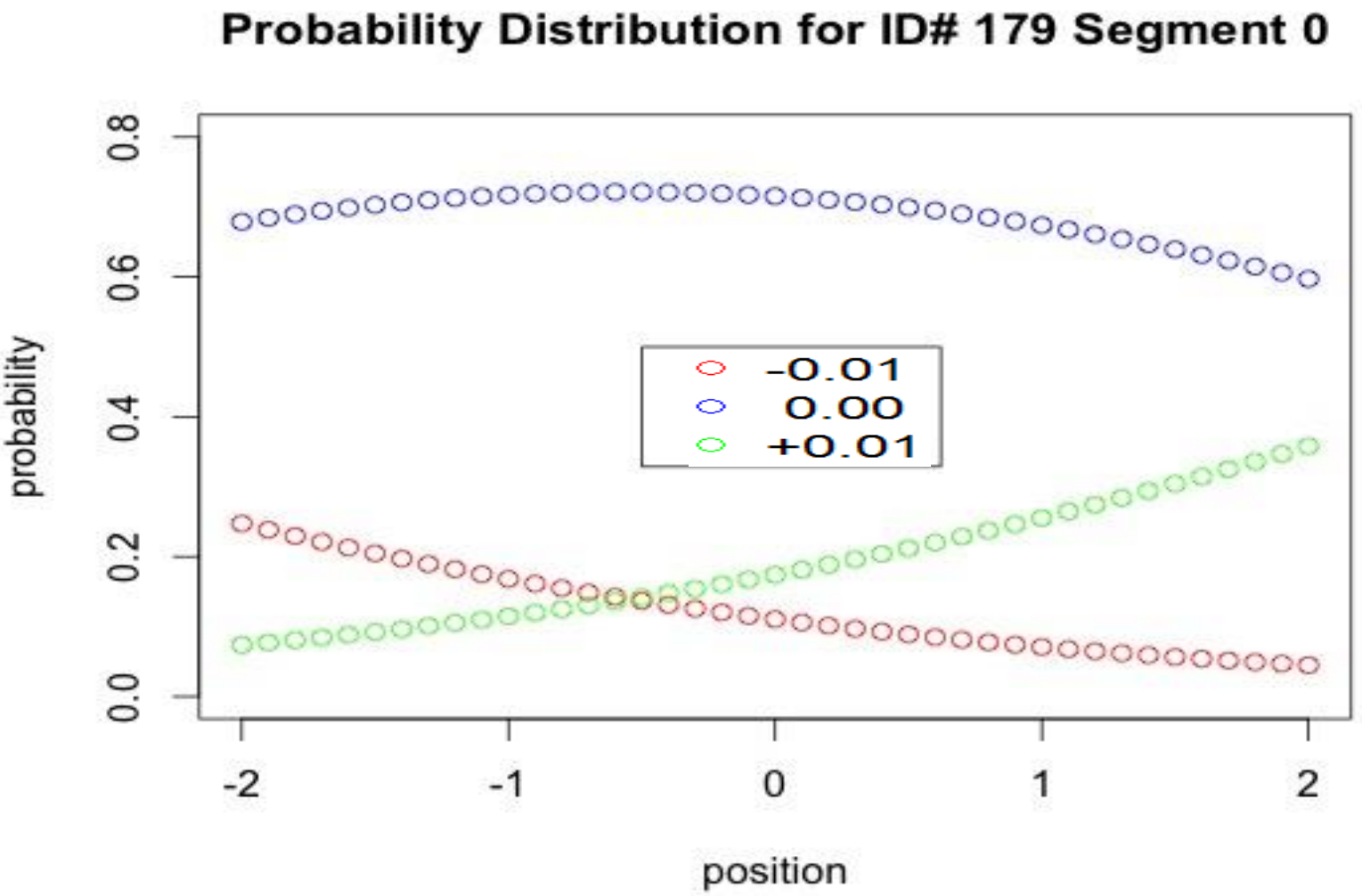
- At each point, there is a probability set (move left, right, or not at all) associated with that lateral position unique to the participant.

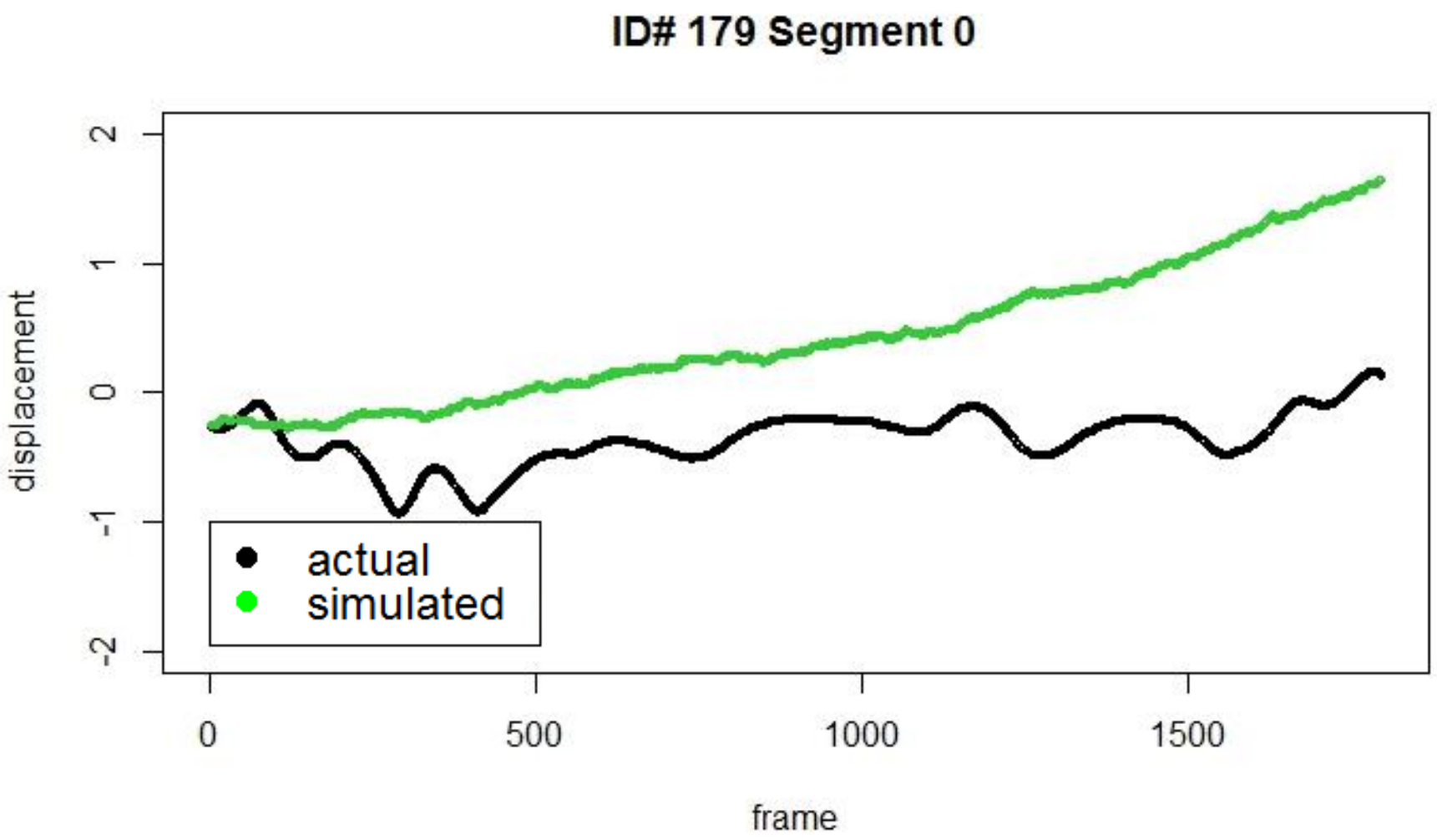
- We used this point probability to attempt to model three data segments:
  - Two randomly chosen participants and a random segment from each
  - One participant and segment which had a model that less resembled the actual data

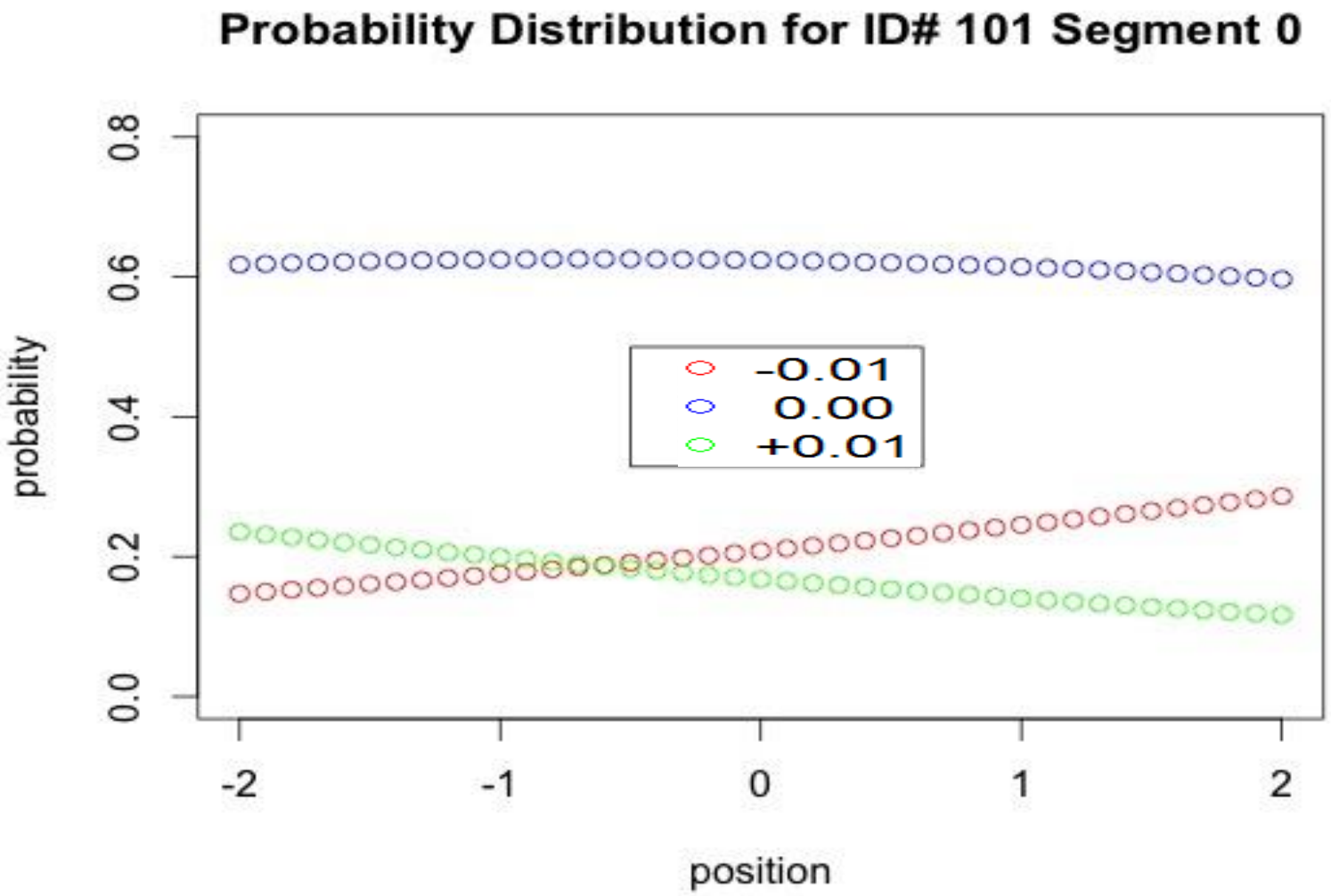

Probability Distribution for ID# 88 Segment 1
probability
0.1
0.3
0.5
0.7
-2
-1
0
1
2
position
-0.01
0.00
+0.01

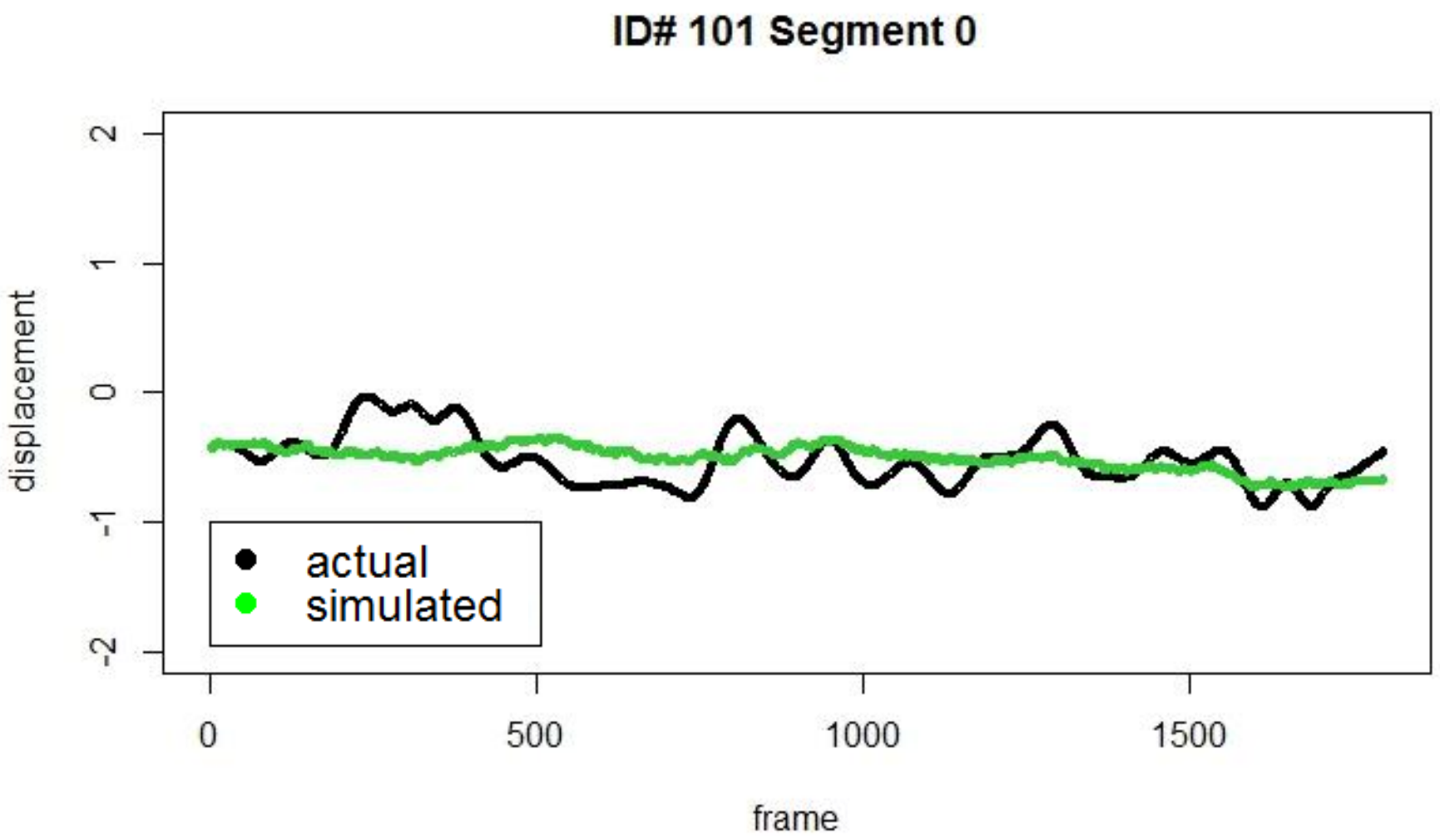
Simulated data




Probability Distribution for ID# 179 Segment 0
probability
0.0
0.2
0.4
0.6
0.8
-2
-1
0
1
2
position
-0.01
0.00
+0.01


ID# 179 Segment 0
displacement
2
1
0
-1
-2
0
500
1000
1500
frame
actual
simulated


Probability Distribution for ID# 101 Segment 0
probability
0.0
0.2
0.4
0.6
0.8
-2
-1
0
1
2
position
-0.01
0.00
+0.01


ID# 101 Segment 0
displacement
2
1
0
-1
-2
0
500
1000
1500
frame
actual
simulated

Method/Analysis of Simulation

- Our simulation uses point-to-point probabilities
  - Realistically, people drive towards one direction for a period of time, rather than changing directions frame-to-frame (1 frame = 1/30 second)
- A possible solution is to use probabilities to determine the period of movement and a separate one to decide direction

- Also, a simulation like the one shown for ID 179 segment 0 gives us a strange model
  - Comparing this to the other segments, participant 179 had increased probability of veering off-center when farther from the center while participants had decreased probability for the same situation.

Thank You…

- Dr. Matthew Rizzo, University of Iowa, for allowing us to use this data
- Dr. Jeffrey Dawson for mentoring us on this project
- ISIB coordinators, graduate students (Terry Kirk, Dr. Gideon Zamba, and everyone else involved)
- You, the audience