Modeling Lateral Position of Driving

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December 14, 2023

Introduction

In the field of driving simulator studies, there is a need for accruate and informative models for infrence. Many reserchers use the Standard Devation of Lane Position (SDLP) as a primary statistic for classifying drives. However, this statistic drastically reduces the information from driving simulators, resulting in a large loss of statisitcal power. There has not been much reserch into more complex and powerful models to handing simulator driving, but in 2010, Dawson et al. proposed a third order autoregressive time series model with a signed error as a new way to model time series [3]. This model was sucesfully able to distinguish bewtween drivers with and without Alzhimers. There are two part of this model, a projection component, which predicts the next position of a drive based off a linear combination of the past three positions, the signed error component, which models the probability of the projection component over or under predicting the true path is model using a logsitic regression.

Including the origonal paper [3], there have been two other papers written about this autoregressive model. In 2018, O'Shea et al. wrote a paper describing a new estimation technique, called the Modificed-Single Pass, replacing the orginal single-pass technique [7]. The Modfied Single Pass method was meant to account for bias in the estimation of parameters in the model, and was sucuessfully able to reduce some of the mean percent bias through a simulation study. Also, in 2019, Dawson et al. wrote another paper, investigating other estimation techniques aside from the Modified Single Pass [2]. These included ad hoc and liklihood based techniques, such as a Grid Search and Newton-Raphson algorithim. However, neither of these technqiues were able to out preform the Modified Single Pass in reducing the bias in parameter estimation.

In this paper, we investiate the model as decribed in [7], specfically the residuals of the projection component and their impact on bias innate in the model. To account for serial autocorrelation found in the signed error component, we add another predicitor to the logisitc model for the sign of the projection error. However, we also found that the distribution of the projection component errors was misspecified, which we belive adds to unnaccounted variablilty in simulation studies. We therefore deceided that for simulations, we should use bootstrapped projection residuals, rather than misspecifed errors. To test the impact of our two modifications, we ran a simulation study, selecting 1000 sets of parameters from a sample multivariate normal distribution defined by real data and generating 1000 drives each. We generated data as described by the Dawson paper, as well as generating data by also bootstrap the magnitude of the projection residuals in order to have more realsitic drives

Our simulation study was centered on determining if our two changes to the original model had any impact on the mean percent bais (MPB) in λ_1. We found that for the original data generation method, there was almost no change to the MPB model with and without lateral velocity. However, generating data with bootstrapped projection residuals, there was a noticeable decrease of about 1-2% in the MPB for larger values of λ.

Methods

Proposed Model

We now turn to a discription of the model proposed by O'Shea an Dawson [3]. For a single simulated drive, let Y_t be the lane position at time $t = 0, 1, 2, \dots, T$, where $Y_t > 0$ represents the left side of the lane, $Y_t < 0$ represents the right side of the lane, and $Y_t = 0$ represents the middle of the lane. In this model, the vector $[Y_{t-3}, Y_{t-2}, Y_{t-1}]$ is reparameterized to $[W_{1t}, W_{2t}, W_{3t}]$, where

$$\begin{aligned}
W_{1t} &= Y_{t-1} \\
W_{2t} &= Y_{t-1} + [Y_{t-1} - Y_{t-3}]/2 \\
W_{3t} &= 3Y_{t-1} - 3Y_{t-2} + Y_{t-3}.
\end{aligned}$$

W_{1t} represents a flat projection, W_{2t} a linear projection, and W_{3t} to a quadradic projection. These projections predict the next point in the time series as if the lateral position, veleocity, or acceleration is mantained, as estimated by the past three points. The vectors, $\mathbf{W}_1 = [W_{14}, W_{15}, \dots, W_{1T}]^T$, and similar for $\mathbf{W}_2$ and $\mathbf{W}_3$, can then be calcualted based on all time positions. With this reparameterization defined, we now look at the thrid-order autogregressive time seris model proposed by O'Shea and Dawson, called the OSD model from here on out [3], defined below:

$$Y_t = \beta_1 W_{1t} + \beta_2 W_{2t} + \beta_3 W_{3t} + |e_t| I_t, \text{ for } t > 3.$$

In this autoregressie model, the β_i's are constrained such that $\beta_1 + \beta_2 + \beta = 1$ and $0 \leq \beta_1, \beta_2, \beta_3 \leq 1$, so that each predicited position is a weighted average of the flat, linear, and quadradic projection, plus an error term.

This error term is the product of two componenets, a magnitude component and a sign compopnent. The magnitude componenet is assumed to be normally distribted with mean of zero and variance of σ_e^2, which is estimated from the model. The sign component is an indicator variable which represents the residual of the projection model: when $Y_t < \hat{Y}_t$, where $\hat{Y}_t$ is the predicited position at time t, $I_t = -1$ with probabtiliy p_t, and when $Y_t > \hat{Y}_t$, $I_t = 1$ with probability of $1 - p_t$. In [3], the functional form of p_t was characterized by the logisitc regtression model:

$$\log\left[\frac{p_t}{(1 - p_t)}\right] = \lambda_0 + \lambda_1 Y_{t-1},$$

where λ_0 is the intercept term and λ_1 is the slope term. In [3], λ_1 is intepreted as the 're-centering' parameter, where higher values indicate a higher tendancy to return to the center of the lane. Although in [3], there was some interpratation of how different values for β_1, β_2, and β_3 relate to a drivers preformance, [7] and this paper, foucs on λ_1 to determine how well a driver preforms.

Estimation

[7] decribed a new method for estimating the parameters of the model above, called the Modififed Single Pass, which was a improvment on the original Single Pass method proposed in [3] in regard to decreasing mean percent bias. The algorthim for MSP (Modified Single Pass) begins with calculating $\mathbf{W}_1, \mathbf{W}_2$, and $\mathbf{W}_3$ based on the first, second, and third lags of the position of a drivers path. The values of the $\hat{\beta}_i$'s are then calculated using OLS, without an intercept term. However, in order to ensure that $\hat{\beta}_1+\hat{\beta}_2+\hat{\beta} = 1$ and $0 \leq \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3 \leq 1$, the values of $\hat{\beta}_2$ and $\hat{\beta}_3$ are remapped to fit to these constrains, and $\hat{\beta}_1$ is set equal to $1 - \hat{\beta}_3 - \hat{\beta}_2$. An estimated path is calcualted then using the projection vectors $\mathbf{W}_1, \mathbf{W}_2$, and $\mathbf{W}_3$, along with their respective values of β. In symobols, we get,

$$\hat{\mathbf{Y}} = \hat{\beta}_1 \mathbf{W}_1 + \hat{\beta}_2 \mathbf{W}_2 + \hat{\beta}_3 \mathbf{W}_3.$$

The reisual vector is then calcualted, with $\mathbf{Y} - \hat{\mathbf{Y}} = \hat{\mathbf{e}}$ and an indicator vector is then calcualted based on the sign of the reisudal, with $I_t = 1$ when $Y_t < \hat{Y}_t$ and $I_t = 0$ when $Y_t > \hat{Y}_t$. The probability of the resiual being negative is then estimated using logisitc regression, with

$$\log\left[\frac{\hat{p}_t}{(1-\hat{p}_t)}\right] = \hat{\lambda}_0 + \hat{\lambda}_1 Y_{t-1}.$$

[3] paper uses Firths ias reduction logisitc regression to overcome either quasi or complete seperation. We follow suit and use this method instead of the GLM method in R. The value of the varaince of the model, $\hat{\sigma}_e^2$, is calculated by traditional means, using the sum of squared differences. The equation is:

$$\hat{\sigma}^2 = \sum_{t=4}^{T} \frac{(Y_t - \hat{Y}_t)^2}{T^* - 3}, \text{ where } T^* = T - 3.$$

A detailed account of the psuedo-code for the estimation and data generation process that we used can be found in [7].

Analysis of OSD Model

In our investiagtion of the model proposed by O'Shea and Dawson, we found two impoortant inconsitiancies: a lack of normallity of the residuals of the linar model of the projections and correlation within the sign of those residuals. We belive that some of the bias that the O'Shea and Dawson group has incountered may be due to these two actributes. The distribution of the resiudals is important for simulation and infrence, such as confidence intervals. The correlation of the sign of the residuals is very importnat, since they are the response variables for the logisitic regression, and correlation in the observations lead to inflated standard errors, and, as we will show, an increase in bias.

Correlation of Residuals

In the OSD model, the sign of the residual of the projection model is vitial in the estimation of λ_0 and λ_1. The sign of the residual indicates whether the model is over or under prediciting the path, and is associated with changes the drivier makes to the cars position in the lane. λ_1 is therefore given a significant amount of importantce for determining differences in dirvers. However, when plotting the drive path with color representing the sign of the residual, we found bands of the same color, with very little random/indpendnet points of differnt color (See figrue 1). These bands indicated that lane position is not the only predictor in the sign of the residual. It also points out that the sign of the reisuals of the projection model are not indepndent of each other. This correlation in the sign of the residuals has a considerable impact on the estimation of λ_0 and λ_1, as well as the interpretation of the model as a whole.

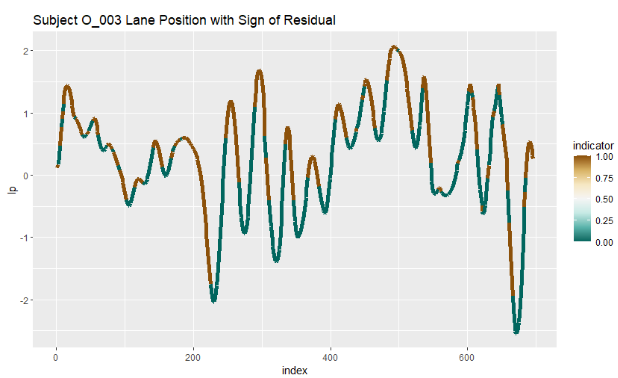

Figure 1

The correlation found in the sign of the residuals of the projection model results in corrolated residuals in the logsitic model, inflating standard error estimates for each coefficent. We also hypotheisized that the autocorrelation in the logisitic model residuals could be impacting the bias in the estimates. In maximum liklihood estimation of linear models, the bias of the ML estimate grows at the rate of $O(n^{-1})$ [6]. However, if the errors are correlated in a model, then the effective n, the number of independent errors, is dramaticially reduced. This provides a theoretical reason for why as correlation between resiudals increases, the bias also increases. We decided to emperically test this hypothesis for λ_1, since in was unclear what our "true" n would be for the logistic model. We therefore created multiple synthetic datasets of indicators, meant to simulate the residual indicator from the OLS model. For simplicity's sake, we modeled the drive as a sine curve with an amplitude of three and calculated the sign of the resiudal based on the same log-odds as the OSD model. However, we added in a correlation parameter, which, for the specificed probability, set the ith value of the indicator equal to the $i-1$th value. We were therefore able to match the bands of the same value of the indicator seen in the true data (See Apendix, Figure 1). Using this parameter, we were then able to change the total amount of correltion in the sign of the residuals for a simulated drive. We found that as the correlation increased, from 0 correaltion to .9 correlation, the bias of the λ_0 and λ_1 estimates increased when the "correlation" probability reached .6, and was significantly higher at .9 (Figure 2). This emperically showed that autocorrealtion in the logsitic residuals leads to biased estimates of λ_1.

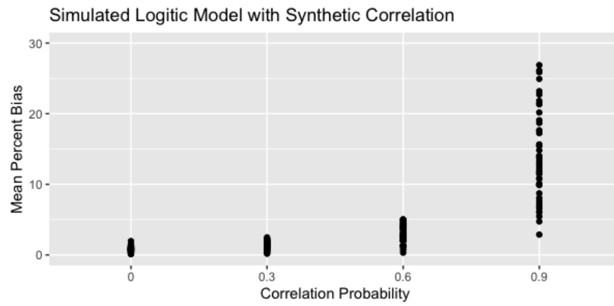

Figure 2

Distribution of Residuals

While studying the diagonsitic plots of our application of the OSD model, we found that the residuals of the projection model were not normally distributed. We compared the histogram of residuals of the projection model to a normal distribution with a mean of 0 and a variance equal to that estimated from the model. There was a noticable difference between the normal residual histogram and true residual histogram. To be specific, the tails of the distribution of the true residuals were much heavier than the normally distributed residuals (See the histogram and QQ plot in Figure 3 and 4). The main effect of mispecification of the projection residuals is that the simulated drives will have a different type of variability in the driving path. In the case of our simulation study, by assuming that the projection residuals are normal, when they are not, there will be a larger discrepancy in the simulated drives for a given set of estimated parameters. We hypotheiszed that the incorrect distribution of the projection residuals may be such changes in the driving paths that parameter estimates are being biased. We hope that by boostrapping the residuals, the simulated driving paths are more consitiant and could produce less biased estiamtes.

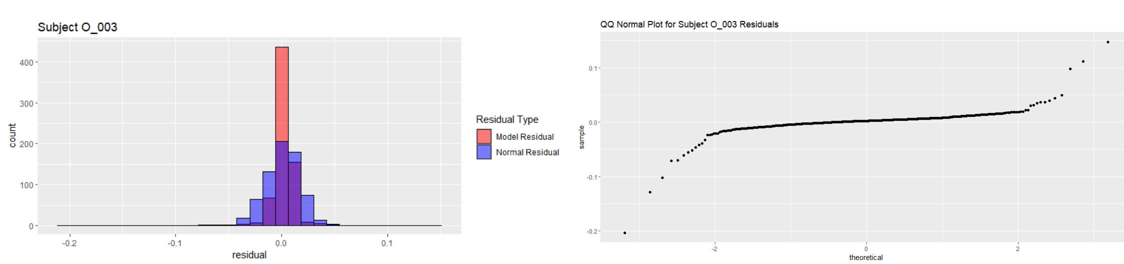

Figure: 3 and 4

Our Proposed Changes

For the two issues we found in the application of the OSD model, we propose one change to the model, and one change to simulation technqiue. For the model, we propose adding in the lateral velocity to the logisitc model. In our analysis of the sign's of the projection component residuals, we found that there was a relationship bewteen the shape of the drive path and the sign of the reisual. For instance, when a path "takes an excursion" from the center of the lane, going to the left/positive values of Y_t, the sign of the residual is negative, until just before the local maximum of the parobola that the path makes, where the sign of the residuals becomes positive, until just before the next local minimum of the path (See Figure 2). This pattern, which appears is most driving path, indicates that we should include some measure of the shape of the driving path into the logistic model. We belive that by adding lateral velocity of the privous point to our logisitc model, the shape of the path will be incorperated into prediciton, leading to more accurate estimation. This model, called the LV model, has a functional form for the probability of a negative residual, p_t, as,

$$\log\left[\frac{p_t}{(1-p_t)}\right] = \lambda_0 + \lambda_1 Y_{t-1} + \lambda_2 V_{t-1},$$

where V_{t-1} is the lateral velocity at time $t-1$. However, the parameter of interest will still be λ_1. Estimating the same real drive with the original model and the LV model, the parameter estimates for $\beta_1, \beta_2, \beta_3$ and σ are all these same, but λ_0 and λ_1 do have different values (Figure 3).

Real Drive Parameter Estimation

Original Model vs LV Model

Type	beta1	beta2	beta3	lambda0	lambda1	sigma
Original	0.05590029	0.2595608	0.6845389	-0.5679039	0.4567025	0.00929247
LV	0.05590029	0.2595608	0.6845389	-0.6112553	0.4991876	0.00929247

Figure 3

Our proposed change to the distribution of the residuals is to not assume any distributional form and to use non-parameteric boostrapping of real drives residuals for the projection residual magnitudes. Since the distribution of the errors has no impact on the model fitting, but only for simulation, we decided to turn to bootstrapping the residuals from real drives for simulation. We only bootstrap the magnitudes of the projection residuals, so as not to impact the sign of the residuals. Therefore, the only impact that this change will have is on data generation during our simulation study. Our intention is to remove any bias in the estimation of λ_1 that may have come from variation in simulated drives.

Simulation Study

Introduce Data

For our simulation study, we used driving simulator data from the University of Colorado, where about 100 participants took multiple drives in mutliple different scenarios. The dataset we worked with had 96 drivers each driving for about 3 minutes. The raw data was camptured in about 60 hz, but we averaged every 5 frames to get data in about 6 hz. After first estimating all 6 parameters for each driver using the orginal model, we recongized that the joint distirbution of all 6 parameters was approximatly multivaraite normal. Therefore, to increase our number of subjects, we created a MVN distribution based on a mean vector and variance-covariance matrix calcualted from the parameter estiamtes from our driving dataset.

Simulation Technique

We ran two simulations, both comapring the model proposed by OSD and the model we have proposed in this paper, which adds in lateral velocity to the logsitic model. In the first simulation, we generate data according to the OSD model (see [7] for an overview of generation technique), and in the second simulation, we instead bootstrap the magnitude of the residual from a true drive. In the simulation which bootstrapped the magnitudes of the residuals from true drives, we first found all true drives which had a variance within $\pm.005$ of the sampled variance. From these sets of parameters, we then found the true drive with the euclidian distiance of all 6 parameters closest to that of the sampled parameters. Then, instead of sampling the magnitudes of the error from a normal distribution with a set variance, we instead sampled from the reisudals of the true drive. For both simulations, we first sampled 1000 observations from the MVN distribution we described above. These sets of 6 parameters can each be though of as a specific drive. We then generate 1000 drives based on the respective data generation model and estimate the parameters with the OSD model and our model. For each set of 6 parameters, we then calcualte the mean, vairance, bias, mean squared error, mean percent bias, and the approximate coverage rate for the OSD model and our model.

Results

The results of our two simulation studies can be found in plots (whatever number plots). Looking at plot (showing difference between models), where we have the differnce in mean percent bias between the LV and OSD model, with normal data generation, for values of λ_1 over 0, we see that the values hover around 0, getting closer and closer and λ_1 continues. However, when we generated data by bootstrapping true residuals, we see that for values of λ_1 greater than .25, the difference between the LV and OSD model is negative, indicating that the MPB of the LV model was less than the Dawson model.

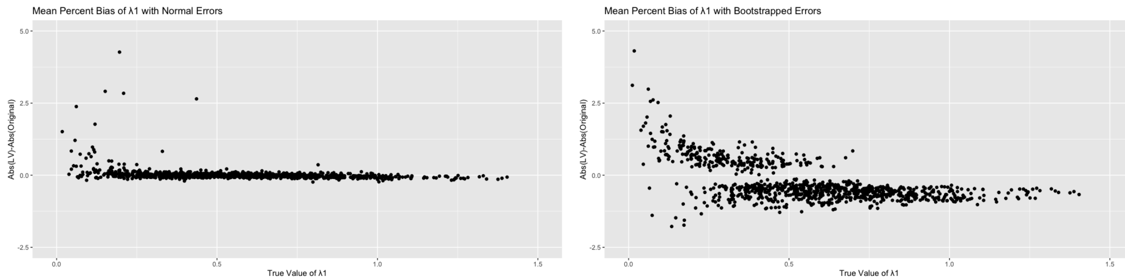

Figure: 4 and 5

Discussion

The time series model proposed by O'Shea and Dawson has clear problems in estimation of parameters of high relevance (λ_1). Our investigation into the effect of correlated errors in the logistic model points out that not only are the standard errors impacted by correlation, but as the correlation increases, the bias of the estimation also increases. This bias has been unaccounted for in previous work [3, 7, 2]. In our simulation study, we found that with the data generation method described in [7], including lateral velocity in the logsitic model had minimal impact to the mean percent bias. As λ_1 increaesed, the difference between the models with and without lateral velocity hovered around 0. However, when generating data with bootstrapped error magnitudes from true drives, there was a minimual, but noticiable decrease in mean percent bias when including lateral velocity in the logistic model. Since the data for this simulation was generated with bootstrapped residuals, the simulated drives had errors which more accuratly represented reality. Therefore, by making the simulated drives more similar to real drives and by including the lateral velocity into the logistic model, there is reduction in the bias of the estimation of λ_1. However, looking at the characteristics of the simulated drives with and without boostrapped residuals, it was very difficult to decern a differnece in statsitics such as range and SDLP. But, based on the histograms of normal residuals vs real residuals, we see that the real residuals have much heavier tails. It follows then that there may be high leaveraged points in the real residuals which are unaccounted for when generating data with normal residuals.

Although we were able to find a small decrease in bias for estimates of λ_1, there are still issues in the model which are unnacoutned for. First off, our inclustion of lateral velocity in the logistic model was based on the visual impact that the shape of a driving path has on the sign of residuals. However, in our investigations, we found that there was no decrase in the autocorrealtion of the residuals of the logsitic model when inclduign lateral velocity. We also noted that there is still a large varaition in drive paths for the same set of parameters, even when bootstrapping residuals from a real drive. Although we tried to account for this variablity in our simulation by running 1000 drives per set of parameters, it is difficult to understand how this variation impacts our simulation results.

Taking a step back, there is still autocorrealtion in the residuals of the logisitc model which are influening both the bias and standard error of the estimates, which impact infrence using this model. It is important that studies which use this model account for these two large impacts to hypothesis tests. There is also still bias in the estiamtes of the β parameters which is not accounted for in our LV model.

Application

We applied both the OSD model and the LV model to driving data concerned with the impact of Cannabis. Our goal was to determine: if λ_1 can pick up impairment in driving, if there is a difference in the OSD model and LV model, and if there is a notable difference in driving preformance - proxied by the recentering parameter, λ_1 - before and after consumption of cannabis.

Data

The data for our analysis came from the University of Iowa Driving Saftey Research Institutue [4]. 30 induviduals were recruited to participate in 4 drive sessions, one baseline and three dosed. The basline was taken first, then each subject consumed about vaporised cannabis. The subject then had three different driving sessions, 30, 60, and 180 minutes after doseage. Each drive had 8 senarios. Our analysis focused on three senarios: Dark, Gravel, and Rural Stright. There were 23 men and 7 women, with a median age of 32.5 years. During the 90 days leading up to their driving, participants reporated that, on average, they used cannabis about 50% of the days. In the 30 days prior to the study, participants reported driving an average of 4.6 days (SD: 8.0 days) within 2 hours of using cannabis. Two-thirds of participants (N=20) reported driving at least once within 2 hours of using cannabis during this period. Additionally, 21 participants agreed with the statement that they could drive safely after using cannabis (14 somewhat agree, 7 strongly agree), and 4 participants believed they were a better driver after consuming cannabis [8].

We compressed our driving data to 5hz to allow for faster and more accurate parameter estimation. The data was processesd using the OSD model as well as our LV model. The λ_1 values for each of the dosed drives were then centered by subtracting the baseline drive to compare the change in λ_1 across dosages. There was a significant amont of driving between senariors, leading us to treat three driving senarios in each driving session as independent. We also verfyied that Senario was not a significnat predictor of $\triangle\lambda_1$ in our analysis.

Methods

We used linear mixed effects regression to model our data. Each subject had about 9 observations. We therefore requried a framework that accounted for the aditional variation within each subject. Mixed effects regression adds flexiblity to analysis by treating specified groups with their own intercept and slopes, termed random intercepts/slopes. The group specific intercept/slope model captures within group variation that a tradional linear model could not. We treated each subject as a group. Due to the small group size, mixed effects regression is better suited than other group comparison methods, such as an ANOVA model [10].

Our analysis was done in R using the lmer package [9, 1]. We used a random intercept model with fixed slopes with each subject representing a group (n = 9). The small group size restircted our use of random slopes. Our analysis began by investigating the post dose response of the λ_1 parameter using a intercept only model. We also analyzed drive number and senario type to determine their assosiation to $\triangle\lambda_1$. Based on past liturature, we hypothesized that change in blood content of delta-9 THC from basline to post-dose, self reported readiness to drive, and how much the enjoyment of the effect of the cannabis could be significant predictors for $\triangle\lambda_1$ [8]. To test the relationship between $\triangle\lambda_1$ and our hypotheiszed predictors, we built two models, one with only readiness as a predictor, and another with all three predictors, and an interaction between enjoyment of the high and change in blood THC content. The models are as follows:

$$\begin{aligned}
&\text{Model 1:} \quad \triangle\lambda_1 = \alpha_i + \beta_1 \text{Ready} + \varepsilon \\
&\text{Model 2:} \quad \triangle\lambda_1 = \alpha_i + \beta_1 \triangle\text{THC} + \beta_2 \text{LikeEfx} + \beta_3 \triangle\text{THC} \cdot \text{LikeEfx} + \beta_4 \text{Ready} + \varepsilon,
\end{aligned}$$

where $i = \{1, 2, \ldots, 30\}$ represents each subject.

Results

Each driver had nine observations with three drives in each of the three senariors. There were drivers who had faulty drives, reducing out total observations (n = 249). The average $\triangle\lambda_1$ on drive 2 was -0.037, $-.045$ for drive 3, and $-.012$ for drive 4.

The random intercept only model with OSD estimates indicates that overall, the λ_1 esitmates post dose are significantly reduced from baseline. The random intercept only model had an intercept coeffient of $-.03$ with a of 95%CI: $(-0.0630 - 0.0005)$. The LV estimates resulted in the same value, but with a larger confidence interval $(CI(-0.0635, 0.0050))$. The OSD estimates are able to capture the differences between pre- and post-dose drives and is responsive to imparement. Incorperating the drive number to the model was indistingusiable from the intercept only model (F-test p-value: .39). Adding a basis spline did not impact the significance of the drive number (F-test p-value: .51). The indistinguishability of the basis spline indicates that there is no nonlinear relationship between $\triangle\lambda_1$ and drive number. As a whole, there is an overall decrease in driving re-centering when intoxicated, irrespetive of time. Using event type as a predictor was not distigusable from the null model (F-test p-value: .15). The indistinguishability of the model with event type supports our assumption that $\triangle\lambda_1$ is independent of event type.

When a driver reported they were ready to drive, on average λ_1 decrased by about .007 (CI: $(-.05, .03)$) from their baseline. However, when drivers were not ready to drive, λ_1 decreased, on average, .05 (CI:$(-.09, -.01)$). These results were found using Estimated Marginal Means using the emmmeasn package in R [5]. Using the LV model, the readiness average remained .007 (CI: $(-0.091, -0.004)$), but the unready average decreased to .048 (CI: $-0.053, 0.042$). Comapring model 1 to the null model, the two models were indistinguishable from each other (F-test p-value: .12). In model 2, our focus was on the interaction between the enjoyment of the high and the change in blood THC content from baseline to intoxication. With one increase in standard devation of both enjoyment of the high and blood THC content, a driver increased their driving preformance by about .002. However, for the LV model, this change was about .001. The result of this interaction indicates that if a person is high and is enjoying the high, then their driving preformance slightly improves. However, if they are not enjoying the high, then their driving preformance slightly decreases. The intercept of model 2 has a coeffecient of $-.049$, which points to when a person has an avaerage enjoyment of the high and the average change in blood THC when they are not ready to drive, their driving preformance is worse than their baseline drive. When comparing this model to the null model, there was not a signfiicnat difference between the two models (F-test p-value: .35.)

Discussion

The random intercept only model verifyed our hypothesis that the re-centering of a vechile is worse after counsumption of cannabis. The lack of significnace of the drive time can be understood there being a variable amount of time that cannabis takes to impact driving and how long it lasts for each person. The majority of drivers were frequent users of Cannabis. Also, a notable number of drivers were confortable driving while high. These subjects are more likley to have a smaller difference in their driving between dosed and non-dosed drives.

The results of the model with readiness to drive point to subjects having a better re-centring ability when they are ready to drive. This finding alings with other research on cannabis [8]. However, the large confidence interval, which includes 0, and the insignificant F-test limit the conclusions we can draw from this analysis. The model with $\triangle$ THC and enjoyment of the high attempted to account for the objective and subjective effects of cannabis. However, due to the small coefficent,the large confidence interval, and insignificant F-test, there is not an apperent relationship between the interaction of $\triangle$ THC and the enjoyment of the drive. There could either be no relationship between this interaction and λ_1, or λ_1 may not be capeable of picking up imparment that is rempresented by self assesment and blood measures.

There were a few key components that may have led to unnotable results for our more complex models. First off, the data set was small: only 30 subjects with about 9 observations each. The high variation of λ_1 across subjects necessitates more data for meaningful results. There is also a learning effect that occurs with driving simulators. As a subject spends more time in the simulator, they become more comfortable in dirivng and their drives become better. Therefore, the increase in $\triangle\lambda_1$ may be accounted by this learning effect. Finally, we only used λ_1 as a resonse variable, whereas in the orinal use of the OSD model, both λ_1 and the β coefficents were used to decern between Alzhimers and non-Alzhimers drivers [3]. In our analysis, we treated the β coefficents as contstant. Since λ_1 is a recentering parameter, or measures the driviers probabilitiy of returning to the center of the lane, there could be a more accurate combination of parameters to measure the overall perfomance of a driver.

The OSD estimates resutled in more percise model estiamtes, whereas the LV model had larger standard errors. However, there were no cases where one estimation method found a decernable result and the other method did. As noted in the simulation study results above, the LV model has less bias than the OSD model for values of λ_1 greater than .5. The λ_1 values for this study were, on average, less than .5 (See appendix, Fig 2). It follows from this result that the OSD method is better suited for this analysis. However, more investigation is required to determine the relative difference in impact of estimation method for data with a wider variety of λ_1.

References

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Appedix

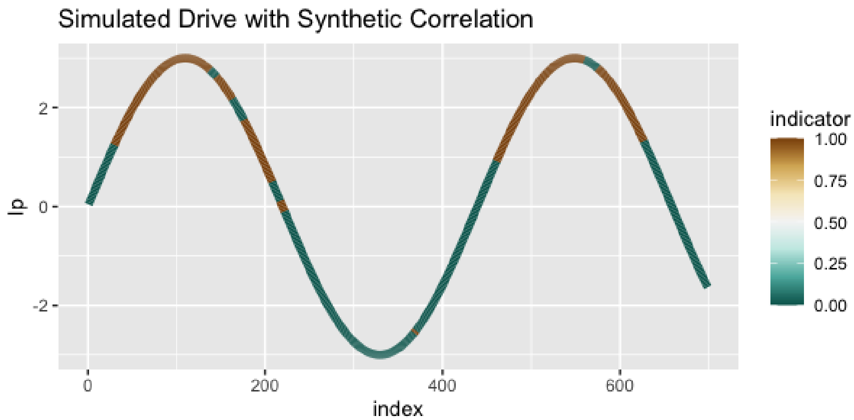

Figure:1

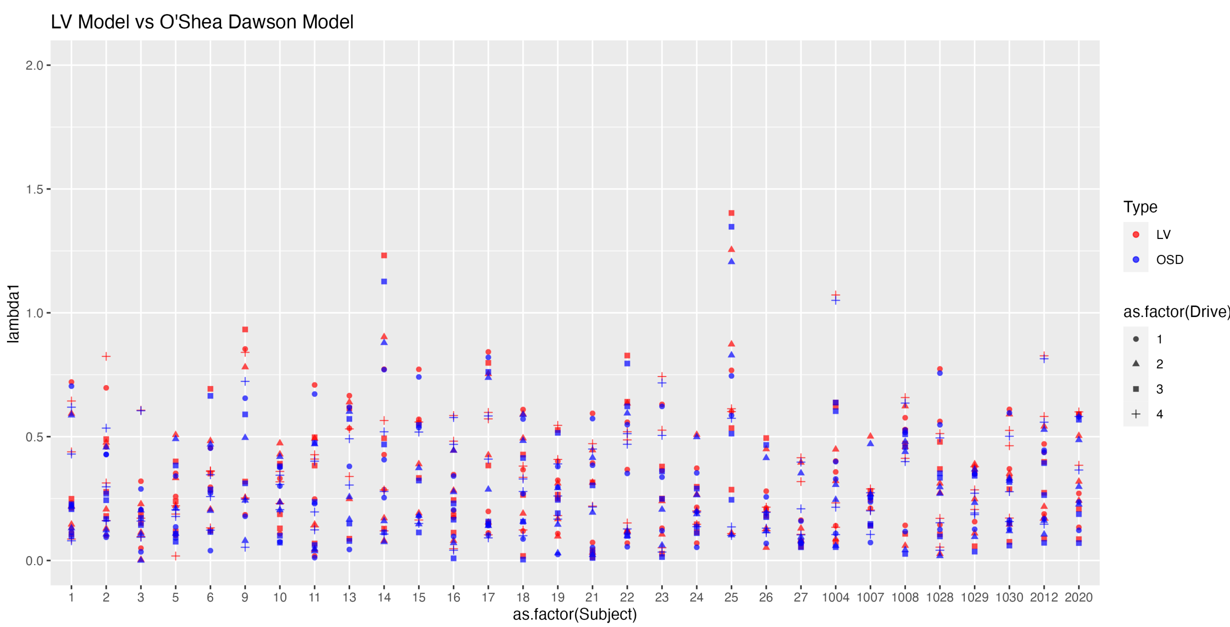

Figure:2