Drift Diffusion Models of children's interactions in a Repeated Prisoner's Dilemma Game (Team 2)

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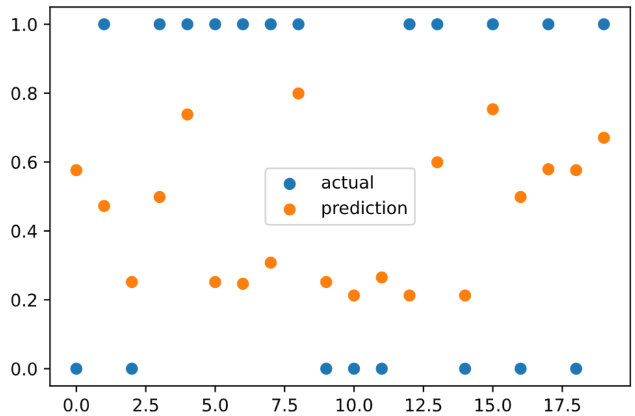
Deliverable 3

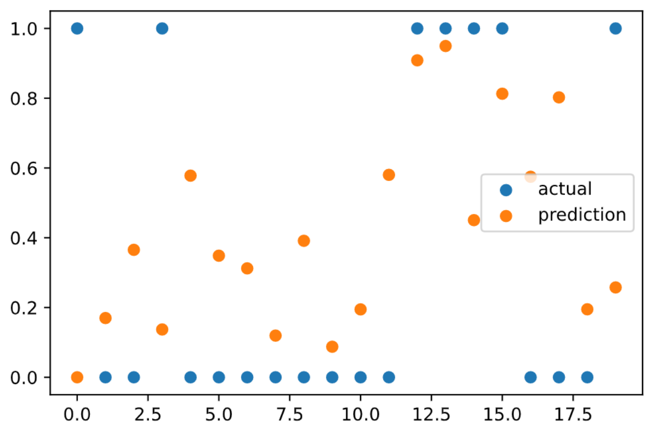
1. Decision Tree Model

Following advice from Steve and Gowtham, we decided to move away from the LSTM model and instead create a decision tree model. Since our dataset is so small, the more complex LSTM model would be susceptible to overfitting by memorizing our limited samples and not generalize well to other data. A decision tree model could be more robust to overfitting given less training data. Our goal for the decision tree model was the same as the LSTM: predict whether a child would cooperate or defect in a given round using information about the child's attributes, specifically aggression, and the decisions of the child's partner in the proceeding rounds. Such a model could provide greater insights into the patterns in the decision making process of the children rather than looking at the total number of times the child cooperated and defected as an aggregate.

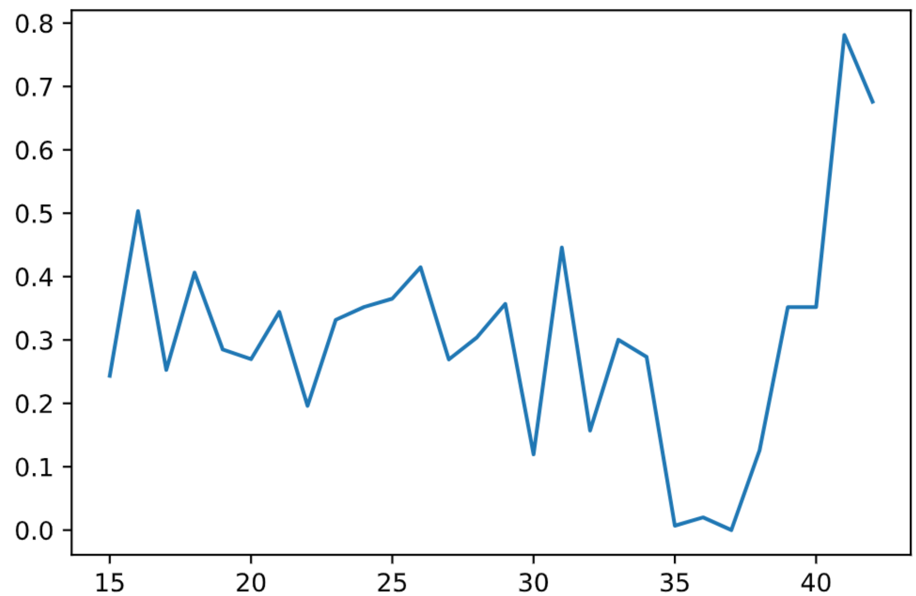
To combat overfitting in our decision tree, we decided to use a random forest model. A random forest is a model made of many decision trees and takes a random sampling of the training data when training each tree, so each tree is exposed to a slightly different subset of the data. Also, a random forest can use a random subset of features when splitting nodes. The prediction of the random forest is the average of each tree's prediction. These characteristics make the random forest more robust to overfitting. We constructed two simple random forest models. The first used the child's self reported aggressiveness and their partner's last decision to predict the child's next decision. The second model used the partner's last three decisions rather than just one. Each model predicted a number between 0 and 1, closer to 0 being more likely to defect and closer to 1 being more likely to cooperate.

Both models could make generally accurate predictions, with the second model consistently making predictions closer to 0 or 1. These figures show the first 20 predictions with orange dots and the actual decisions with blue dots, for our first and second random forest models respectively. The closer the orange and blue dots are for a given index on the x-axis, the more accurate the prediction.





We were hoping this model would allow us to answer the questions “Are children with higher aggressive traits more less likely to return to cooperation over the three rounds after partner defection (less likely to forgive)?” and “Does the partner's deviation from their initial pattern (as pre-programmed) cause a change in state (e.g., preference) in the child?”. Using the model trained on the three previous partner decisions, we constructed various sequences of three moves and tested each across a range of aggression values to see if the predicted behavior was different. Unfortunately, there was no clear linear trend between aggressiveness and the likelihood of cooperation given a specific sequence. For example, these are the results for the sequence “defect”, “defect”, “cooperate” over a range of aggressiveness values:

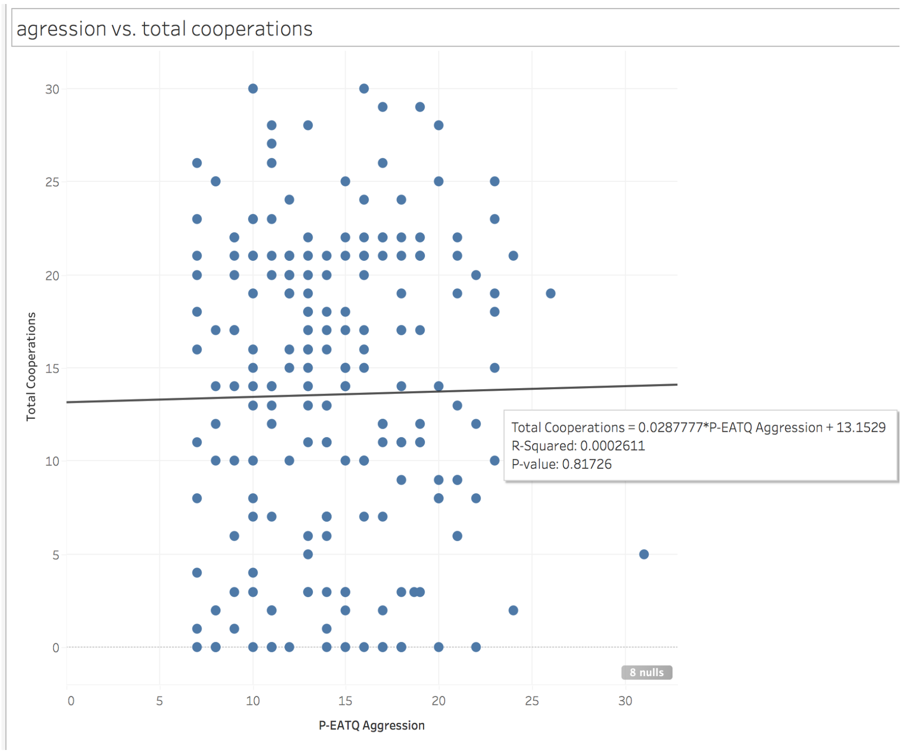


We chose this sequence to test a child's tendency to forgive and cooperate if their partner defects twice then cooperates. If this tendency could be linked to aggression, this would answer one of our key questions. However, the results do not demonstrate any clear relationship here. We hypothesize that this is again due to our lack of data. The random variation in the sample of children that participated in the experiment could be hiding a meaningful relationship.

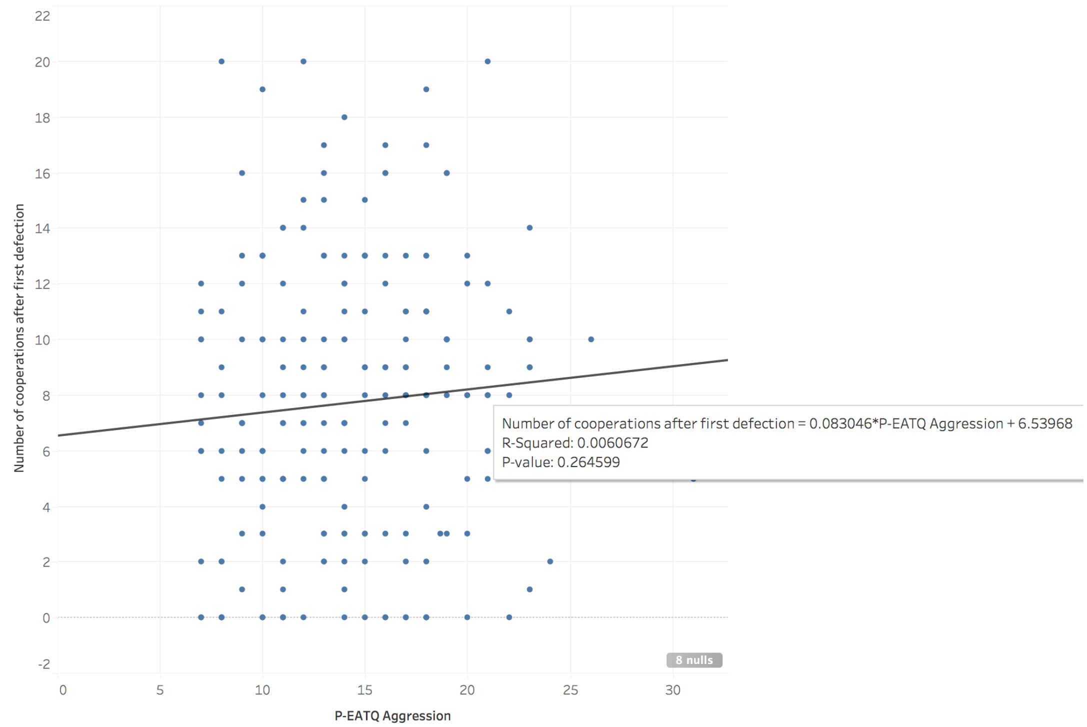
Our regression model - and why we suspect there any clear patterns:

Consistent with what we found for our last deliverable, our regression model did not show any clear patterns between aggression and cooperation/defection (consult Ryan about what regressions were tried in particular). In addition to the python tools, we also created several scatterplots using Tableau to try and better understand this relationship. As shown below, the high p-values and low R-squared values show little to no patterns in the data with regard to cooperation and aggression scores. P-values higher than 0.05 are often used as a benchmark for trend lines showing statistically significant correlations or not, so these very high p-values indicate little to no correlation. To the same effect, R-squared values whose absolute value is close to 1 indicate a perfect correlation between two variables, so low R-squared values indicate low correlation between variables.

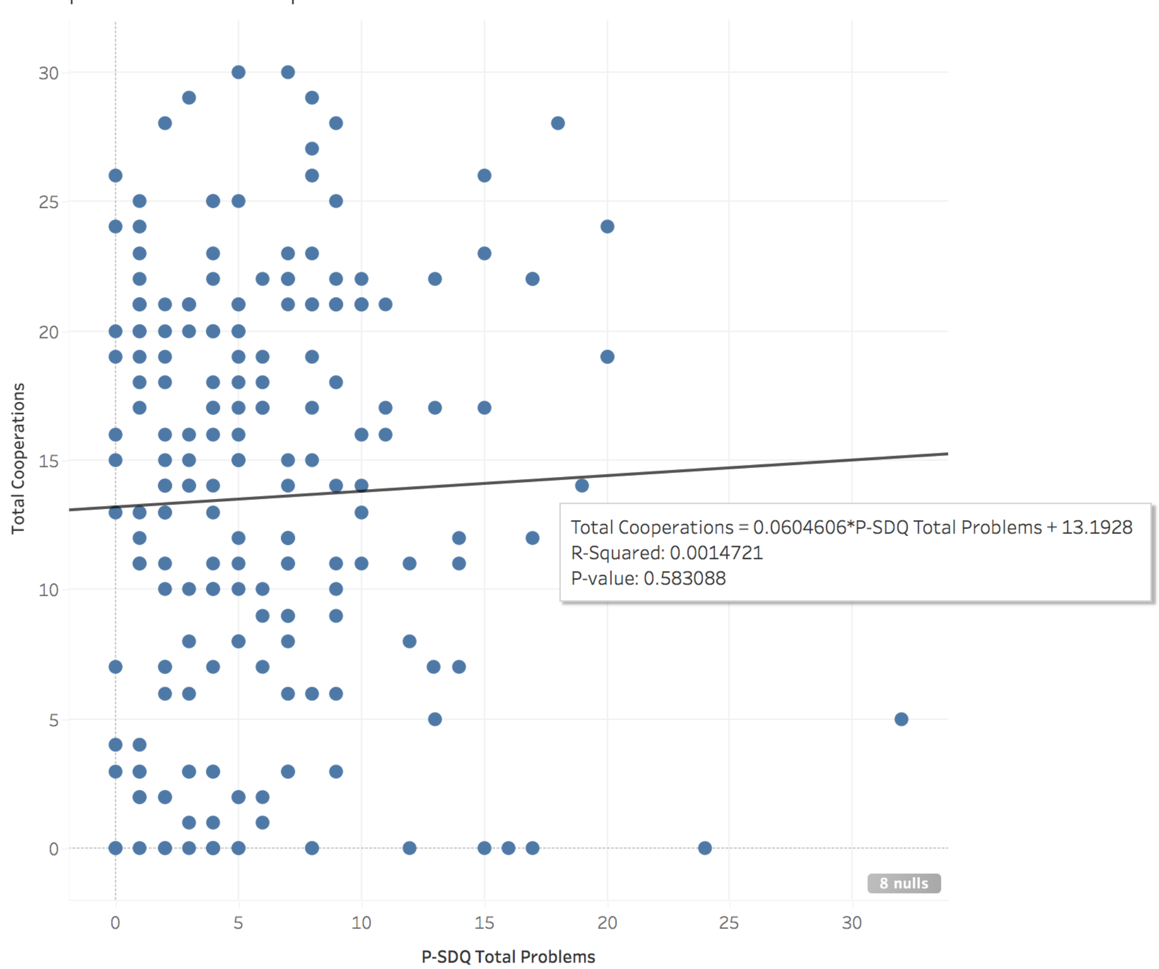
We looked at scatterplots of cooperation after the first defection, and in total across all rounds and found similar results as shown below.



agression vs. cooperation after first defection

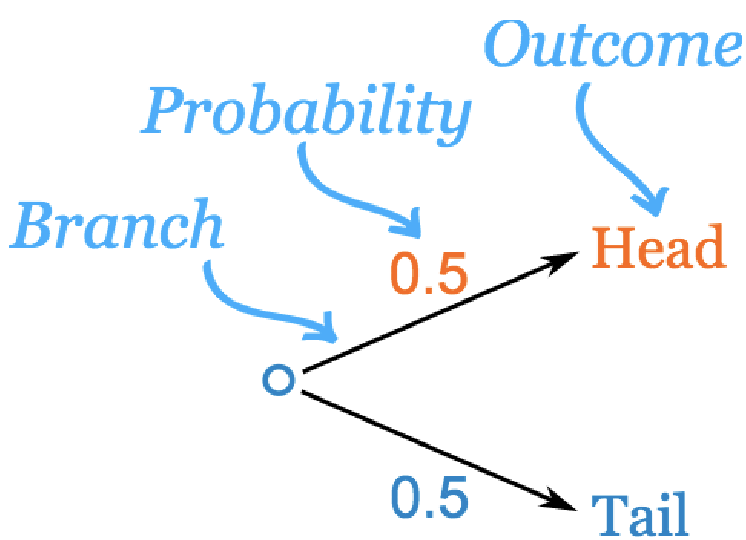


total problems vs. cooperation



As we begin to more clearly see that there was no overwhelming pattern in our data (at least using a regression model), our focus is shifting from trying to find a trend, to trying to explore reasons and more concretely prove that there may not be a trend in our data.

After speaking with one of the project managers Gowtham, we learned that a regression may be a bad fit for our data, because the decisions in each round are connected - so the child's decision to defect or cooperate is related to what they, as well as their partner did for the last round. It is for this reason that he recommended looking into the decision tree model - given that this model predicts future decisions based directly on past events or decisions. An example of a simple decision tree is shown below. This is a decision tree for a coin flip, where 0.5 is the likelihood that it will land on heads or tails for each flip (represented by the node labeled zero).



Potential reasons why we are not seeing strong correlations in our regression models:

- Our data does not follow the assumption for multiple linear regressions which is that the different variables (so the different coefficients) must not be correlated (all our variables should be independent). This may explain why we are not seeing patterns in the data when using the regression approach (talk more about independence in multivariate regressions). When speaking to one of the spark project managers (Gowtham), he suggested using a decision tree model (which depends on what happens in the previous round), as the decision to defect or cooperate depends on the previous round.

- Include correlation matrix - use this to justify/prove collinearity and correlation between variables in our regression model (what were the actual variables used in the regression model?)
- Include new regressions Ryan tried
- Include tableau visualizations confirming the lack of trends and giving potential explanations for why there is no clear correlation between aggression and cooperation

- Mention feature selection using Lasso model - I want to talk about this but I don't know what Ryan ended up using it for
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Limitations with data/risks of achieving project goal:

- As we run more analysis, it seems likely that there is no clear pattern in the data (which is possible with a dataset so small). If this is the case, we still plan on giving our client a detailed report of what we did find, and some possible explanations (along with supporting graphs) detailing why there might not be a clear pattern in the data.

Sources:

https://www.mathsisfun.com/data/probability-tree-diagrams.html

Deliverable 3 assignment description:

Project Deliverable 3 (v1 Final Report)

All data should have been collected. All project questions should have been reviewed, answered, and submitted in a written document outlining findings as a PR. You will also be asked to submit the associated data and a README explaining what each label/feature in your dataset represents. Your team should meet with the client before this deliverable.

Checklist

1. All data is collected
2. Refine the preliminary analysis of the data performed in PD1&2
3. Answer another key question
4. Attempt to answer overarching project question
5. Create a draft of your final report
6. Refine project scope and list of limitations with data and potential risks of achieving project goal
7. Submit a PR with the above report and modifications to original proposal