Impacts of Human Characteristics on Reaction Time (RT) to Visual Stimuli

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Abstract

We used data from Michael Franke's IDA Mental Chronometry dataset to understand the impact of demographic features like age, education, sex and handedness on visual input reaction times (RT). We created two multiple linear regression models, and ran a classifier on one to evaluate its predictive capabilities. Overall, both models were successful at identifying certain significant demographic features that influence RT, and support the need for considerations in accessible design for information systems and digital content delivery.

Introduction

We are consuming visual data at a very fast pace in our everyday lives. With the burgeoning trend of content creation, content creators are pushed to deliver more in less time. This shift on social media is very apparent; we can see more short videos (reels, shorts, stories etc) being promoted than the long ones. It has become a well-known fact that in order to be successful on social media platforms, one must follow this trend to get more hits. Therefore, it becomes important for us to analyse how visual inputs impact reaction times and how information is processed by certain demographic groups. With this knowledge, we can design accessible and useful information systems that effectively deliver relevant content to a wide variety of end users.

The Mental Chronometry Dataset

For this study, we will be using Michael Franke's IDA Mental Chronometry Dataset We have extended the concepts used in the book by taking education and age also into consideration while analysing the data.

The dataset contains entries from 50 participants in the study which records the differences in reaction times across different tasks. The trials have 3 parts: reacting to any stimulus shown (responding with a spacebar for a circle and square), reacting to a specific stimulus (responding with a space bar for only to square/circle), and reacting differently to 2 different stimuli (responding with different alphabets for circles and squares). These are classified as reaction tasks, Go/No-Go tasks and discrimination tasks, respectively. The dataset includes demographic information such as education, age, gender, and handedness in addition to the reaction times and correctness regarding stimulus type.

Summary Plots

Below are a set of plots and a table intended to describe some of the demographic explanatory variables we are interested in for subsequent analysis.

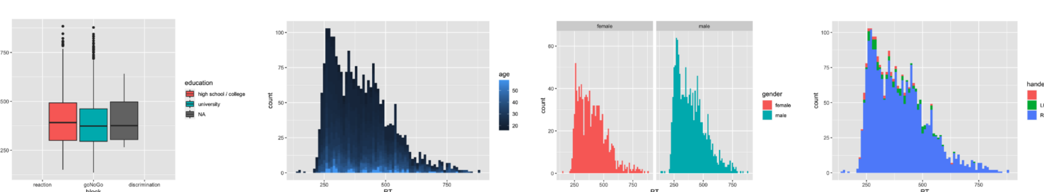

Figure 1: From left to right, histograms showcasing the distribution of the education, age, gender, and handedness variables.

Table 1: Summary statistics of select binary explanatory variables in the sample. For handedness_num, 0 refers to left-handed participants and 1 refers to right-handed participants. For education, 0 refers to participants whose highest completed level of education is high school or a college degree and 1 refers to participants whose highest completed level of education is a university degree. For gender, 0 refers to participants who identify as male and 1 refers to participants who identify as female. Note that null values were excluded from the counts.

handedness_num	n	education_num	n	gender_num	n
0	100	0	924	0	1335
1	2254	1	1430	1	1069

Methods

The dataset had two features of note which we decided to use to assess participants' performance on reaction time tasks:

- The amount of time each participant took to complete one of the three tasks, measured by *RT*.
- The amount of time each participant took to complete all three tasks, measured by *total_time_spent*.

Multiple Linear Regressions

In order to test our research hypothesis, we settled on doing **two multiple linear regressions**, one for each dependent variable. Our goal was determine the strength and character of the relationship between our dependent and independent variables. The mathematical formula for linear regression is as follows: $y = w^T x + b$ where $x = (x_1, \ldots, x_D)$ represents a vector of features that are used as model parameters, y is the dependent variable, w is the weights of the parameters, and b is the bias/line intercept.

Finally, to assess the significance of each independent variable, we assume $\alpha = 0.05$.

The summaries of both models' coefficients and their interpretations can be found in the *Results and Discussion* section.

Feature Encoding

Some of the features in our dataset are non-numeric (handedness, gender and education). The multiple linear regression model works best with numeric variables. Therefore, we used a simple label encoder that turns the target labels to values between 0 and 1. Handedness, gender, and education are numerically represented by handedness_num, gender_num and education_num. These are the variables we used to construct our two regression models.

Correlation Matrices

As mentioned, there are two models we wished to study:

1. Dependent variable being reaction time (RT).
2. Dependent variable being total_time_spent.

The independent variables of interest are: handedness, gender, age, and education. We created a correlation table with each of them and the dependent variable in question, as well as a correlation matrix with all independent variables we considered. See Appendix A and B for detailed outputs of our correlation analysis.

To further illustrate the strength of the relationships between each dependent and independent variable pair, we plotted a simple linear regression of the dependent variable on each independent variable of interest. This resulted in 8 individual plots: 4 for each RT-independent variable pair, and 4 for each total_time_spent-independent variable pair. See Appendix C and D for these plots.

Classification Exercise

We also wanted to understand how well our proposed models could predict whether an individual has satisfactory reaction time. By constructing a classifier and evaluating its performance, we can further confirm if our findings are statistically significant. The *Naïve Bayes (NB) classifier* fits our dataset the best, as our features of interest can be assumed to be independent of each other based on the low values shown across the correlation matrix. The NB classifier assigns labels to observations based on an established prior distribution of labels for a feature of interest, which is determined by the training data. We ran the classification exercise on our *RT* model.

Amano et al. (2006) conducted a study on visual stimulus reponse. They found that participants react to a slight motion approximately 300 ms after it takes place, and that "the neural activites related to finger movement" were offset by approximately 130-200 ms (Amano et al, 2006). Using this finding as a benchmark, 500 ms is our threshold for an ideal reaction time in any given task. For the classification algorithm, we created a categorical dummy variable which sorts each data point into a "good" reaction time and a "not good" reaction time. This will be captured in a variable named *good_reaction*.

We fit an NB classifier to training data, which was a random sample of 80% of the original data set, with observations that had missing values removed. The remaining 20% of the dataset was used as a test dataset to evaluate the predictive strength of the classifier. The classifier was also cross-validated with $k = 10$ fold cross validation. The results of the classification exercise are described in more detail in the *Results and Discussion* section.

Results and Discussion

Model 1: RT on Explanatory Variables

Table 2: Estimated model coefficients and their standard errors, t-values, and p-values for the multiple linear regression of RT on the explanatory variables of interest.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	314.1873739	18.0955822	17.3626563	0.0000000
handedness_num	31.0261037	13.3171146	2.3297918	0.0199033
gender_num	0.3952652	5.3387823	0.0740366	0.9409877
age	2.4881030	0.3151183	7.8957754	0.0000000
education_num	-18.1250757	5.3575292	-3.3831035	0.0007287

Our results displayed above show our intercept, our four independent variables, and their output coefficients with their p values to determine if our variable is statistically significant. The intercept is statically significant and tells us that when all independent variables are set to zero, then reaction time is estimated to be 314.19 ms. Our handedness_num variable is statistically significant and shows that the variable exhibits a positive correlation with RT. The model predicts that right-handed individuals have a reaction time that is 31.03 ms slower than left-handed individuals. Our gender_num variable is not statically significant so we can safely ignore this variable.

Our age variable is statistically significant and the coefficient for age is estimated to be positive correlation with RT. With every unit increase of age, the model predicts that RT will increase by approximately 2.49 ms. The last independent variable, education_num, had a much different result than our other variables, with a coefficient of –18.13. The negative sign is indicative of an inverse relationship with RT. The model predicts that university students had a lower RT than high school and college students by 18.13 ms. The p-value associated with this coefficient is much smaller than 0.05, so this variable is statistically significant.

The reason this type of analysis was done is to see the strength of an outcome or dependent variable, RT in this case, against our independent variables of interest. Handedness had the strongest correlation with RT, whereas gender had the weakest relationship with RT and a p-value above significance level, meaning that it is not a statistically significant factor in predicting one's RT. The most surprising result was the negative effect of education level on RT. We can say that handedness is the most positively correlated while education is the most negatively correlated regarding reaction time.

Model 2: total_time_spent on Explanatory Variables

Table 3: Estimated model coefficients and their standard errors, t-values, and p-values for the multiple linear regression of total_time_spent on the explanatory variables of interest.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.0846133	0.4583397	11.093548	0.0000000
handedness_num	0.8557832	0.3373068	2.537107	0.0112429
gender_num	-0.9191645	0.1352250	-6.797295	0.0000000
age	0.0199508	0.0079816	2.499613	0.0125021
education_num	0.1753357	0.1356999	1.292084	0.1964578

When all the predictor variables are at a value of 0, the total time spent has a value of 5.08, which is also statistically significant as the p-value of 0.00 is less than the significance level set at 0.05. The regression coefficient estimated for the handedness variable has a value of 0.86 which is statistically significant since p-value = 0.01 < 0.05, and therefore indicates a positive relationship where every unit increase of handedness, total time spent increases by 0.86. The regression coefficient estimated for the gender variable has a value of -0.92 which is statistically significant since p-value = 0.00 < 0.05, and therefore indicates a negative relationship where every unit increase of gender, total time spent decreases by 0.92. The regression coefficient estimated for the age variable has a value of 0.02 which is statistically significant since p-value = 0.01 < 0.05, and therefore indicates a positive relationship where every unit increase of age, total time spent increases by 0.02. The regression coefficient estimated for the education level variable has a value of 0.17 which is not statistically significant since p-value = 0.2 > 0.05, and therefore should not be considered.

Overall, this regression analysis allows us to investigate and draw conclusions about the strength of the effect each of the predictor variables (handedness, gender, age, and education level) has on the dependent variable (total time spent) and whether they actually have an impact on total time spent at all. Looking at all the regression coefficient estimates that were statistically significant, we can observe that gender had the largest impact on total time spent as its corresponding regression coefficient had the largest absolute value. Similarly, we can observe that handedness also has a large impact on total time spent, just in a positive direction. Age can be observed to have the smallest impact on total time spent according to its much smaller regression coefficient value. Lastly, the analysis on education level was found to be not significant, which leads to no conclusion on its effect being drawn.

Naïve Bayes Classification Exercise

Results from the classification algorithm being run on test data show that it labelled 371 good reaction times that were actually good (these are true positives). However, there were 89 reaction times that the classifier thought were good but were actually not (these are false positives).

Table 4: Confusion matrix of results from the classifier being run on the test data after it had been trained.

	Good	Not good
Good	371	89
Not good	0	0

The accuracy of the classifier labelling response rates as either good or not good compared to the feature's actual value in the test data was 80.65% accurate. This is good, as anything below 70% is not ideal. This means our model did a good job in classifying which reaction times were actually good and which just appeared to be.

Limitations and Conclusion

Limitations

The principal limitation with our approach to analyzing and interpreting the data is that the causal structure of our explanatory variables and the paths through which they impact RT for an individual task and the amount of time a study participant needed to complete each task in succession is uncertain. It is justifiable to think that while the correlation analysis showed that our chosen explanatory variables had low correlation with each other, there may be confounders external to the study which affect their relationship with each other and with the dependent variable in either model. For instance, older individuals may have been less likely to attend university based on changing job and skill requirements to enter the labour market over time. Alternatively, left-handed individuals don't have as many tools which are designed with their use in mind, impacting their ability to react promptly to the visual stimuli they are presented with.

Another limitation with our methodology comes from the use of multiple linear regression models. Since some but not all of our explanatory variables had to be coded as binary numeric ones, the linear relationship between each of them and the dependent variable based on the model in question is difficult to illustrate, even if it exists as seen in our Appendix plots. We ultimately chose to go with multiple linear regression due to the nature of the raw data and the inconsistency across how their values were recorded. We recognize that a logistic regression would better illustrate the relationship between binary variables and a continuous dependent variable, but with only some variables being binary, it was difficult to justify using a multiple logistic regression for either model.

Both of these limitations would be rectified, or at the very least, mitigated by the inclusion of more descriptive factor levels for the features that had to be transformed. By incorporating more levels into each factor (for instance, including different education levels or an indication of which hand a participant used to complete each task), we can easily visualize the relationships between each independent variable and the dependent variable.

Conclusion

Both models support our hypothesis that the chosen demographic features influenced an individual's ability to immediately and successfully recognize certain visual stimuli and minute changes in them to a statistically significant extent. The results reinforce the importance of considering accessibility in information system design and content creation. While it is difficult to balance the unique needs of everyone who interacts with virtually delivered information and the desire to create systems which promote immediate engagement with content, the findings from this study can motivate the development of assistive tools to help individuals meaningfully interact with the information systems that they encounter.

References

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Franke, M. (2021). *An Introduction to Data Analysis.* https://michael-franke.github.io/intro-data-analysis/app-93-data-sets-mental-chronometry.html

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Appendix

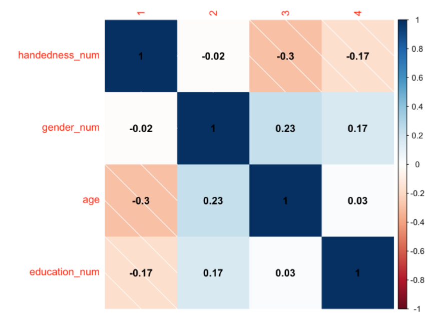
Appendix A:

RT_handedness_cor	RT_gender_cor	RT_age_cor	RT_education_cor
0.0116265	0.0380846	0.1632338	-0.0840391

time_handedness_cor	time_gender_cor	time_age_cor	time_education_cor
0.0345605	-0.1121461	0.0108126	-0.0113043

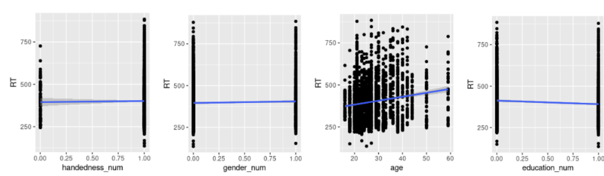
From top to bottom, 1) Pearson's r values for each explanatory variable and the dependent variable RT, and 2) Pearson's r values for each explanatory variable and the dependent variable total__time__spent.

Appendix B:



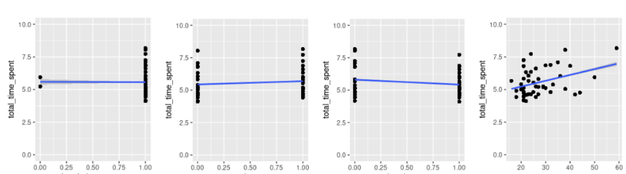
Correlation matrix of all independent variables of interest. Note the low correlation values between many pairs of variables.

Appendix C:



Plots of all independent variables vs. RT. From left to right, the independent variables are handedness, gender, age, and education.

Appendix D:



Plots of all independent variables vs. total__time__spent. From left to right, the independent variables are handedness, gender, age, and education.