# MAT 303 Module One Problem Set Report

Multiple Regression

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To start off this report, I want to first introduce the data set that I’ll be exploring. I will be analyzing the dataset of *Motor Trend* US magazine’s car road tests from 1974 in 10 different aspects of automobile design and performance for 32 different automobiles made from 1973 to 1974. Even though these will be results from cars from 50 years ago, this data will help new manufacturers in the ability to design current vehicles. The reason being is because from this data we can not only estimate what different variables should be, we can also see actual statistical data from these cars since they have been around for that long.

I will start off by visually exploring different comparisons in scatterplots, to a Pearson Coefficient matrix of variables, and then writing a multiple regression model equation to use with this data. From here, I will be looking at the comparisons of and adjusted , what a fitted value and residual is, and my assumptions on the homoscedasticity and normality of these residuals. At the end, I will be looking at the created model to see if it is significant at the 5% level, looking the overall F-test, and then interpreting this model for the different hypotheses I will give, the p-value, and the overall conclusion of the tests.

Next here, I would like to introduce the important variables that I will be using in this dataset. I will be looking at fuel economy in miles per US gallons, gross horsepower, and weight. These three variables will be referred to as MPG, HP, and WT, respectively. In the entirety of the dataset, there would be 32 rows and 12 columns, but I am not looking at everything.

For the first visuals, I want to show two different scatterplots. One being of fuel efficiency against weight, and the other being fuel efficiency against horsepower.

Chart, scatter chart

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Looking at both graphs, one can see a visually negative correlation between both HP and WT to fuel economy. What this means is that the higher that either WT or HP go, the lower the fuel economy is going to be. We can also look at a matrix of this with the Pearson Correlation Coefficients here:

Table

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One can look at this matrix and see the negative correlation between the two variables to the response (MPG). After looking at the regression algorithm for this, it will make more sense.

Speaking of the algorithm for the multiple regression model, this is what it would look like: which in my case would be **.** Looking at this regression model printout, the numbers here can be explained.

![Text, letter

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generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RD6RXhpZgAATU0AKgAAAAgABAE7AAIAAAAQAAAISodpAAQAAAABAAAIWpydAAEAAAAgAAAQ0uocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJlbmphbWluIExlYW5uYQAABZADAAIAAAAUAAAQqJAEAAIAAAAUAAAQvJKRAAIAAAADNjYAAJKSAAIAAAADNjYAAOocAAcAAAgMAAAInAAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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From the original model, and are represented as the coefficients of the variables WT and HP, respectively, while is represented by the coefficient of MPG. This model interpretation means that on average, the MPG of the automobile drops by 3.878 for each unit increase in the WT. These measurements in weight are also in the thousands (for example, a WT of 3.878 equals 3,878lbs.) Also, for each unit increase in HP, MPG would also drop by 0.032. Looking farther into the model’s printout, we get:



While both are similar, there is a difference in them. The value is a statistical measurement that represents the proportion of the variance of a dependent variable that’s explained by one or more independent variables in the regression model. What this means is that since we have an of 0.8268, approximately 82.68% of the observed variation can be explained by the model’s input. The adjusted value is a more precise, modified version that has been adjusted for the actual number of predictors in the model. While the values are based off the entire model with all variables included, the adjusted values are based off testing different independent variables against the dependent. This means that the adjusted value can be biased while the regular cannot.

Next, I would like to analyze the fitted values and the residuals. Our fitted values, in this instance, are going to be the predicted value of the dependent variable (MPG) for data points from the data set. The residual values are the difference between the actual value of the variable (MPG) and the predicted value. To get a better look at this there are two more plots I want to visually show, a plot of residuals against fitted values, and a normal Q-Q plot.

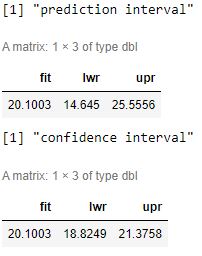
Chart, scatter chart

Description automatically generatedChart, scatter chart

Description automatically generated

On the left plot, you can see a homoscedasticity pattern throughout instead of a heteroscedasticity pattern in the shape of a fan. Again, in the Q-Q plot, since the plots are tight about the line, one can assume that linearity and homoscedasticity are met. If it were in violation, you would see a tight fit about the bottom of the line and fanned out more toward the top.

In this last evaluation, I want to check to see if the model is significant at a normal 5% level of significance. To start this, I want to explain the null hypothesis and alternate hypothesis and how this level of significance is measured to select the correct one. The null hypothesis here will be that there is no correlation between the independent variables (WT and HP) to dependent (MPG). In the alternate hypothesis, one would want to see at least one of the independent variables have a correlation to the dependent. In mathematical speaking, the formula would look like this: where the alternate would be To measure this we will use the p-value of each independent variable to see if we should reject or not. From the coefficient’s table where I made the regression algorithm, the p-value of WT is 1.12e-6 and the p-value of HP is 0.00145. Comparing these two to the level of significance (5% or 0.05), both are with the range (0%-5%) so I will reject the null hypothesis and assume that there is, in fact, a correlation between the independent variables to the dependent.

 From here, I will create a 95% confidence interval for the variables WT and HP and explain them.

The confidence interval at 95% here says that from all the values from our dataset, 95% of them will fall in this model and 5% will not. I’ll explain why this is in just a bit, but first, let’s test my model. If I were to predict the MPG for an automobile that has a WT of 2.95 (remember, this is 2,950lbs) and an HP of 179, I can use my regression algorithm and plug this in: My model says that the MPG of this car should be approximately 20.06. Using the 95% confidence interval the MPG would be approximated between 18.8 and 21.4 with the 95% prediction being 14.7 and 25.6. The reason that my prediction interval is wider than the confidence interval is simply because it expresses more uncertainty. While the confidence interval takes the actual known data, our prediction interval is from our model of possible unknown future estimates. Remember, the model’s (confidence) was just above 82%, not 95%.

In conclusion, after performing all these tests and analyzing the results, I am confident that I would recommend this model for business use in certain aspects. I don’t believe that this model has enough information for the number of technological advances and changes the world has seen in the last 50 years. For just one simple comparison, according to fuelly.com, a 1974 F-100 (smaller than a new F-150) got approximately 7.63 MPG with a HP of 160 and WT of 3.55. A 2022 F-150 (larger) has a WT of 4.02 and HP 400 but still get an MPG average of 22.5. The information is, in my opinion, a good starting point to create a better model.

## Citations

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