# Predicting world happiness

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- ► DS-300 METHODS OF DATA SCIENCE & ANALYTICS

May 4th 2021

# Predicting World Happiness

- We will be using multiple linear regression and polynomial regressions to build a ladder score in order to predict world happiness.
- since we are using multiple linear regression we will also be using backwards elimination.

## Looking at the Data set

- used two data sets from a collection of data sets from Kaggle.
- the data is from the years of 2020 and 2021
- uncleaned, the data sets start off with 20 variables.

# Cleaning the Data Sets

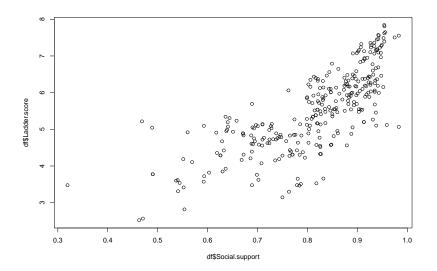
- Began with renaming the columns to match the variables.
- Then columns were removed. These inculde Standard.error.of.the.ladder.score, upperwhisker, lowerwhisker, Ladder.score.in.dystopia, Explained.by.Logged.GDP.Per.Capita, Explained.by.Social.support, Explained.by.Healthy.life.expectancy, Explained.by.Freedom.to.make.life.choices, Explained.by.Generosity, Explained.by.Perceptions.of.corruption, Dystopia.Residual, Country.name, and Regional Indicator.
- ▶ Then finally we bind the datasets together.

## Why these were removed

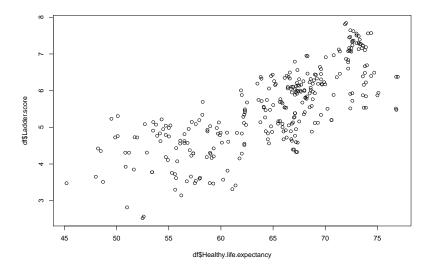
- Country.name was removed because it holds about 150 unique variables.
- Regional.indicator removed because it holds 9 different variables
- All variables starting with explained, and Dystopia. Residual were removed because there was no information on what they were.
- Removed Standard.error.of.the.ladder.score, upperwhisker, and lower whisker because they were not relevant variables for our research question.

#### **EDA**

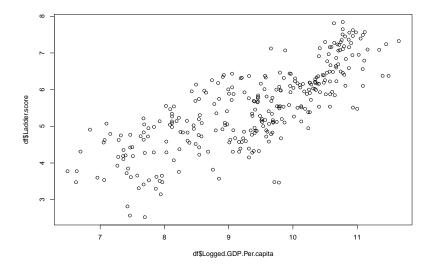
plot(x = df\$Social.support, y = df\$Ladder.score)



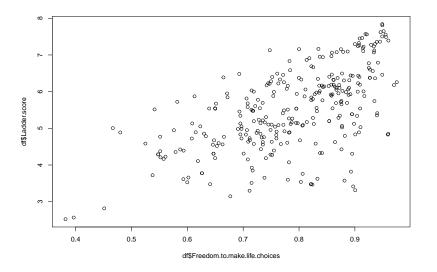
plot(x = df\$Healthy.life.expectancy, y = df\$Ladder.score)



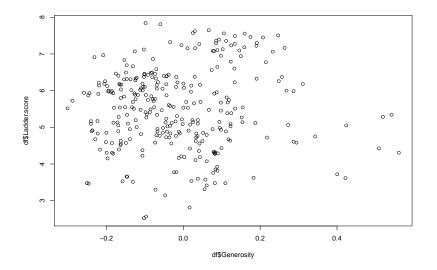
plot(x = df\$Logged.GDP.Per.capita, y = df\$Ladder.score)



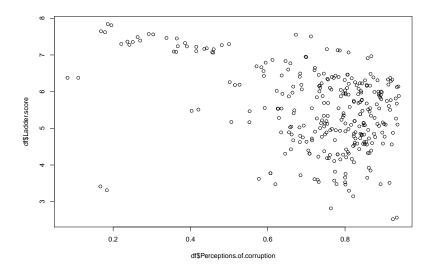
plot(x = df\$Freedom.to.make.life.choices, y = df\$Ladder.sc



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plot(x = df$Generosity, y = df$Ladder.score)
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plot(x = df\$Perceptions.of.corruption, y = df\$Ladder.score)



# Multiple Linear Regression

- ▶ All variables were made to be numeric if they weren't already.
- split the data into training and test sets
- All remaining variables were written into the formula for multiple regression

# Backwards elimination for the multiple Regression

- ► We chose a p value of .05 for backwards elimination, and only one variable exceeded that p value
- Generosity exceeded the p value and was removed. And no other variables exceeded the p value after Generosity was removed, so that was the end of backwards elimination

# Results of Multiple Regression

▶ Looking at the adjusted R value of .7388 from the summary of our regression, we can say that this is a decent model to predicting Happiness. If we could increase the adjusted R value our model would be an even better fit.

# Polynomial Regression

- We decided to do polynomial regression as well since some of the scatter plots in our Exploratory Data Analysis look like the could follow the line of a parabola.
- The variables that followed that shape were Social.support, and Healthy.life.expectancy.
- ▶ So we fit those two to polynomial regression.

# Backwards Elimination for Polynomial Regression.

- ▶ We began by removing Perceptions.of.corruption because it exceeded the p value by almost 20 percent.
- ▶ We then had to do backwards elimination on Generosity because it was also greater than the p value, although it was very close to it. We could have kept it since it was close .05 but we decided to get rid of it.

# Results of the Polynomial Regression

- ▶ We then pulled the summary of the polynomial regression and looked at the reported adjusted r value, which is .763.
- Before backwards elimination our adjusted R squared was .764.
- ► Ultimately not much change occured when removing the variables Perception.of.corruption, and Generosity.

# Comparing the Two Regressions

▶ When we compare the adjusted R squares of each of the regressions we can see that the polynomial regression would be better at predicting world happiness than the Multiple regression would be.