Prenatal Diet and Pregnancy Weight Gain

STAT 471 Final Project

Sam Simon and Vicki Li

December 19, 2021

Github Repository Link:
https://github.com/samsimon12/pregnancy-weight-gain-final-project

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Executive Summary

Maintaining a healthy prenatal diet is essential for ensuring infant health and avoiding birth defects, both of which have linkage to pregnancy weight gain. Eating certain food groups in surplus may cause unhealthy weight gain, which increases the risk of long-term health issues for the child. Given this information, we decided to look at various nutrients and see how the distribution of their intake during pregnancy affected pregnancy weight gain. Although weight gain is expected in pregnancy, we recognized that there was still significant merit in analyzing certain food groups to see which ones were more likely to contribute to excess weight gain, which is something that would lead to health complications for both the mother and child.

The dataset we used was sourced from a diet history questionnaire as part of the Infant Feeding Practice Study II, which included basic socioeconomic data, some health history about the mother, and how frequent and how much the mother ate a specific food. After tidying the data, we chose our response variable as weight gained during pregnancy, as it predicts prenatal diet quality extremely well. Our explanatory variables were among two categories: socioeconomic and health-related factors, and nutrient intake factors.

To begin with our analysis of the data, we used 80% of the clean data for training, and reserved the last 20% for a test data set, which we would use to evaluate the performance of our models. We also checked the residuals beforehand in order to ensure that regression would run smoothly. For our analysis, we chose 3 different methods: ordinary least squares regression, ridge regression, and random forests for tree-based methods. OLS regression and ridge regression had similar test errors, but random forests had the lowest test error out of the three methods.

Each method did have a disparity between which features were the most important in analysis, but low pre-pregnancy BMI was unanimously a predictor of high pregnancy weight gain among each model. For random forests and ridge regression, the amount of white potato servings was also positively correlated with pregnancy weight gain. Since random forests provided the most accurate prediction, the foods we concluded from that model that were most indicative of pregnancy weight gain were white potato servings and trans-fatty acids.

Given this information, we recommend that researchers examine the association between pregnancy weight gain and infant health complications, as its correlation with pre-pregnancy BMI implies its importance in predicting health outcomes. We also believe that the specific foods our models pointed to as pregnancy weight gain predictors should be researched further to balance out the trade-off between nutritional value and unhealthy weight gain.

Introduction

During pregnancy, the fetus obtains all of its nutrients through the mother, making the mother's prenatal diet crucial for the healthy development of the infant. Excess and lack of specific nutrients may have long-lasting deleterious effects on the growth of the child, which may lead to long-term health consequences. However, the quality of the prenatal diet within the United States is low, with pregnant women in the National Health and Nutrition Examination and Survey 2003-2012 scoring 50.7 points out of 100 on the Healthy Eating Index-2010.[1] As a proxy for the quality of prenatal diet, extensive research has been done about pre-pregnancy BMI (body mass index). Women with normal pre-pregnancy weight have been found to have higher prenatal diet quality than women with pre-pregnancy obesity.

Although there has been significant research linking the risk of a poor prenatal diet with a woman's pre-pregnancy BMI, BMI is a static predictor, meaning it assumes that a woman's diet through pregnancy will remain unchanged.[2] As a result, we were interested in studying how weight gain during pregnancy is related to diet - although pregnancy weight gain, just like pre-pregnancy BMI, has shown clear associations with prenatal diet quality, there has been little research on it comparatively. Since pre-pregnancy BMI is a well-researched risk factor for poor prenatal diet quality, we wanted to examine how they correlated with pregnancy weight gain, and if the two factors follow the same predictive patterns.

In addition, we sought to understand how varying amounts of nutrient intake would affect pregnancy weight gain. In order to ensure a healthy pregnancy, pregnant women have many recommended medical guidelines to follow, such as how many calories they should ingest per day or how much of one food group they should eat. Specific minerals and vitamins, such as folic acid, are beneficial to reduce the probability of birth defects.[3] The United States has long focused on BMI in their research studies to predict the quality of prenatal diet because of the increasing prevalence of obesity. To both contribute to elucidating the role of pregnancy weight gain and spotlighting the issue of obesity, our project aims to see which specific nutrients, such as calcium or sodium, contribute the most to weight gain during pregnancy. We hope to shed light on specific foods that may result in excess pregnancy weight gain, which has strong correlation with negative child health outcomes.

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[1] WO;, S. D. (n.d.). Pre-Pregnancy Weight Status Is Associated with Diet Quality and Nutritional Biomarkers during Pregnancy. Retrieved from https://pubmed.ncbi.nlm.nih.gov/26978398/

[2] Parker, H. W., Tovar, A., McCurdy, K., & Vadiveloo, M. (2019, October 18). Associations between pre-pregnancy BMI, gestational weight gain, and prenatal diet quality in a national sample. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6799919/#pone.0224034.ref037

[3] Nutrition During Pregnancy. (n.d.). Retrieved from https://www.hopkinsmedicine.org/health/wellness-and-prevention/nutrition-during-pregnancy

Data

Data Source

We obtained our data from a paper exploring the associations between pre-pregnancy BMI, gestational weight gain, and prenatal diet quality, which was available to us through the US National Library of Medicine and National Institutes of Health.[4] The data itself was based on a diet history questionnaire that was sent out to 1322 pregnant women in the United States that assessed both the frequency and amount of different food groups that they ate during the third trimester of their pregnancy as well as various questions about past health history and socioeconomic status. The questionnaire itself was part of the Infant-Feeding Practices Study II, which was conducted by the FDA and CFC from 2005-2007 and aimed to study mother and infant from the third trimester through the first year of the infant's life.[5].

Data Cleaning

Cleaning our data set mostly consisted of modifying the entries by getting rid of any extra characters. For example, an entry that was originally "f: 2 times per week" would be tidied into "2 times per week". Some column names were also very long and not indicative of the actual feature being analyzed, so we renamed them to more accurately reflect their contents. We also removed columns that we thought would not be relevant to the response variable (amount of weight gained during pregnancy), such as features like "the date the questionnaire was received". We also removed all non-numerical values in order to be able to conduct regression analysis properly. To account for any data analysis inconsistencies we removed all N/A entries, and also removed observations that included negative pregnancy weight gains, since the purpose of our study was to find which nutrients were the most strongly correlated with weight gain.

Data Description

After cleaning the data, our dataset had 977 observations, each one corresponding to a different pregnant woman. It contained 32 features, 28 of which were different food groups that the subject had eaten during pregnancy. The other features were pregnancy weight gain, BMI pre-pregnancy, poverty-income ratio, and age of the mother.

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[4] Parker, H. W., Tovar, A., McCurdy, K., & Vadiveloo, M. (2019, October 18). Associations between pre-pregnancy BMI, gestational weight gain, and prenatal diet quality in a national sample. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6799919/#pone.0224034.ref037
[5] Studies of Breastfeeding and Infant Feeding Practices. (2021, August 31). Retrieved from https://www.cdc.gov/breastfeeding/data/ifps/index.htm

Our response variable was the amount of weight gained during pregnancy. We chose to focus on this continuous variable because most of the data is detailing the diet composition of the woman, and we want to explore the relationship between pregnancy diet and pregnancy weight gain. However, it is important to recognize that pregnancy weight is not only dependent on diet, but also other health behaviors of the woman during the gestational period and prior health history.

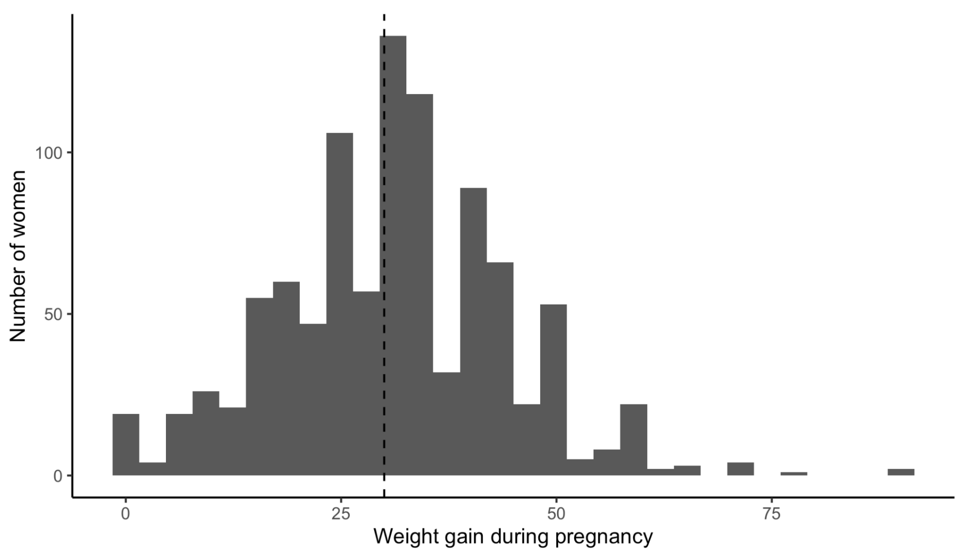
We next decided to look at the explanatory variables in relation to weight gain during pregnancy. The explanatory variables consist of socioeconomic and health data on the mother, as well as specific aspects of the mother's diet history while pregnant (DHP), such as food, nutrient, and vitamin intake. All of our explanatory variables were continuous variables. Please see the Appendix for more information.

Data Allocation

For exploration, we split our data set into a training set, which was used to construct our predictive models, and a test set, which was used to evaluate the success of our predictive models. We allocated 80% of the data for training, and 20% of the data for testing. We also set the seed every time we ran a model in order for reproducible results.

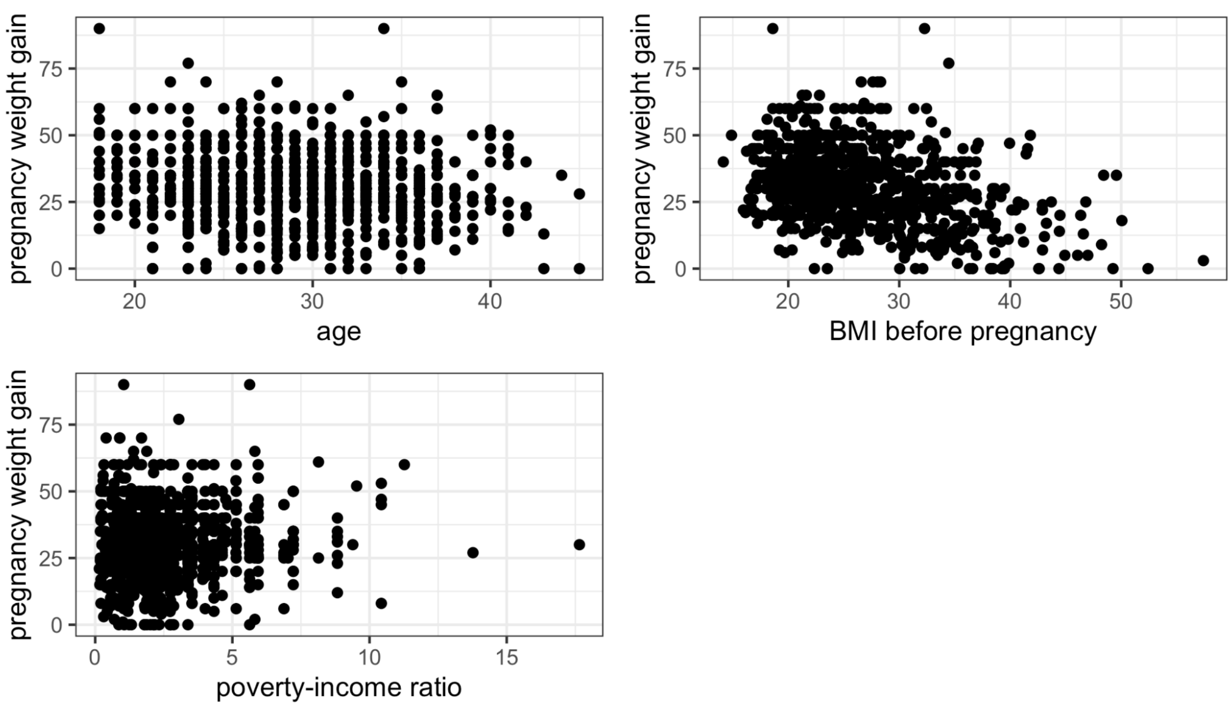
Data Exploration

Our first task in data exploration was to understand the distribution of the response variable. We produced a histogram for pregnancy weight gain among the women sampled in the data set. We can see that the distribution is right skewed, and the median weight gain during pregnancy was 30 lbs.



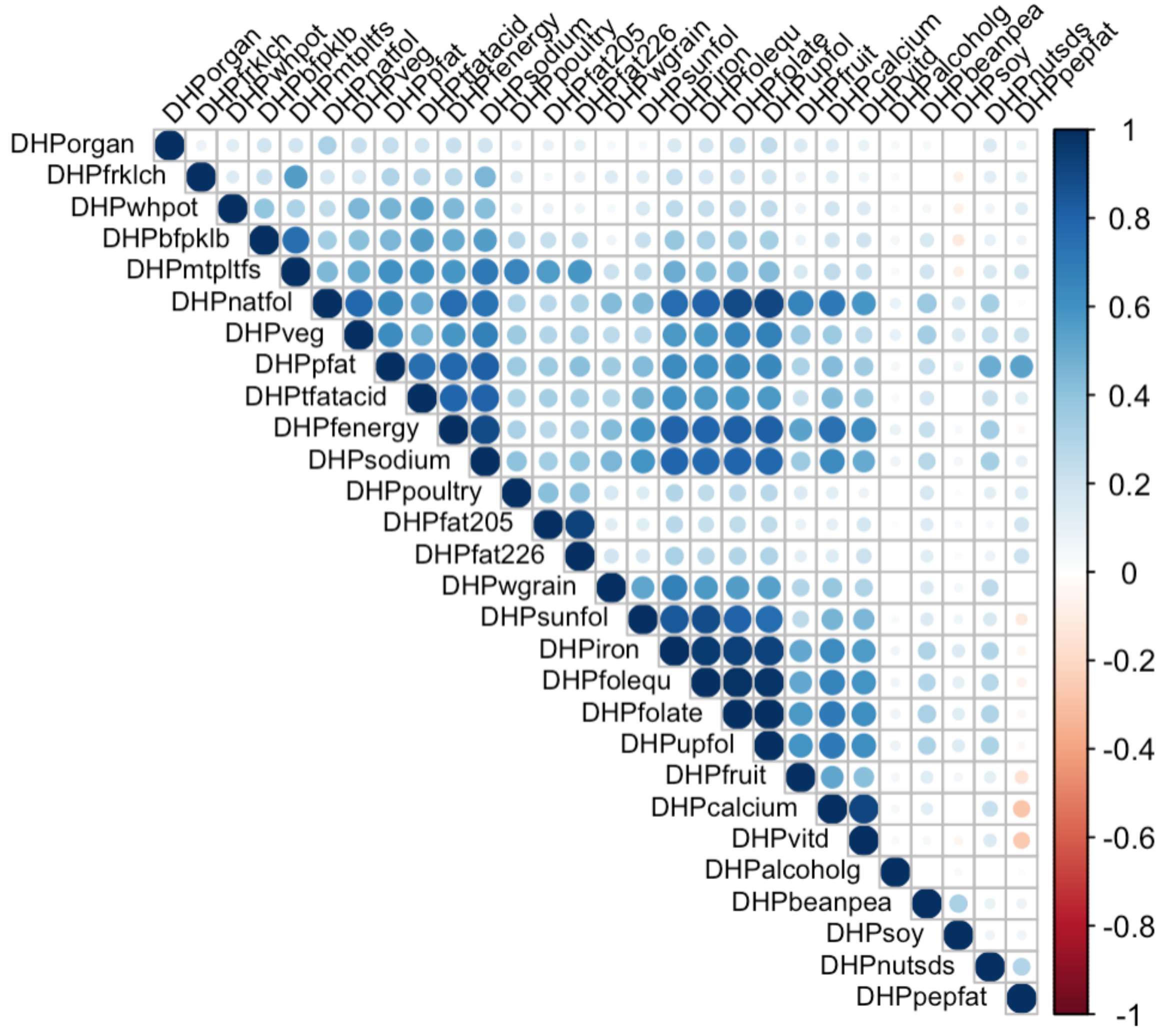
Socioeconomic and Health Factors

Our dataset can be split into 2 types of features: the mother's diet history, and socioeconomic/health factors. To further analyze the latter, we plotted our response variable against age, BMI before pregnancy, and the poverty-income ratio in three respective scatter plots. We observe weak relationships between the socioeconomic factors and weight gain during pregnancy. There appears to be no relationship between age and weight gain, which seems reasonable since most women become pregnant within a similar age range. There appears to be a slight negative relationship between weight gain and BMI before pregnancy. This trend makes sense to me because a lower BMI usually corresponds to a lower weight, and we might expect women who weigh less before pregnancy to gain more during it. There is a slight positive relationship between poverty-income ratio and weight. This trend supports past research linking poverty and obesity. However, a more in-depth analysis would need to be performed in order to determine the validity of that association in our dataset.



DHP Correlations

Next, we can observe the correlations between some of the DHP variables, which each correspond to a specific nutrient or food that the mother has eaten during the third trimester, as depicted in the correlation plot below. While most of the correlations are sparse, select DHP variables are correlated. Various variables related to folate intake, such as natural folate and updated folate, are highly correlated, ranging from 0.97 to 0.99, which makes sense as they are measuring similar features. Features that are related to folate also have the most aggregate correlation with other variables, such as vegetables, polyunsaturated fats, calcium, and sodium.

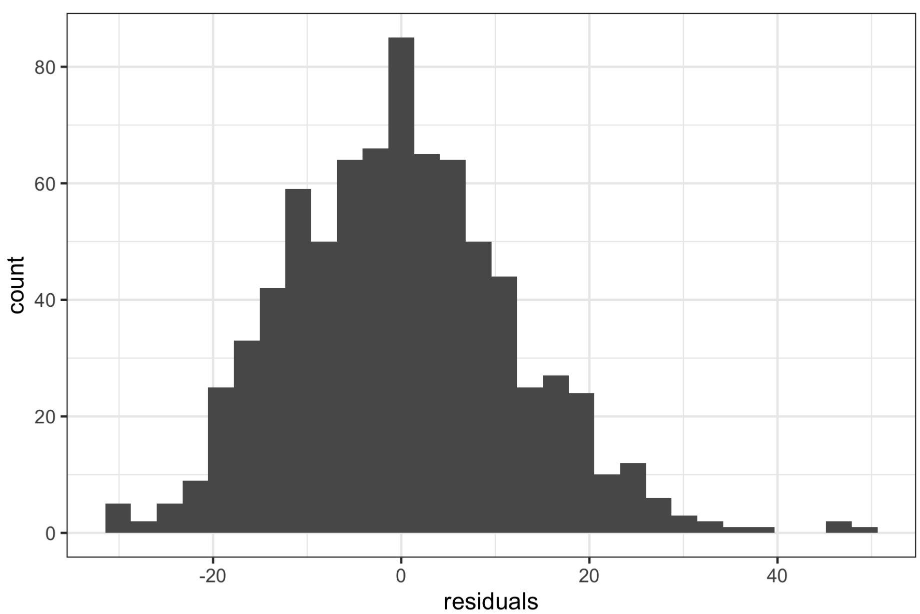


Modeling

For our three statistical machine learning methodologies, we chose ordinary least squares regression, ridge regression, and random forests to analyze our data.

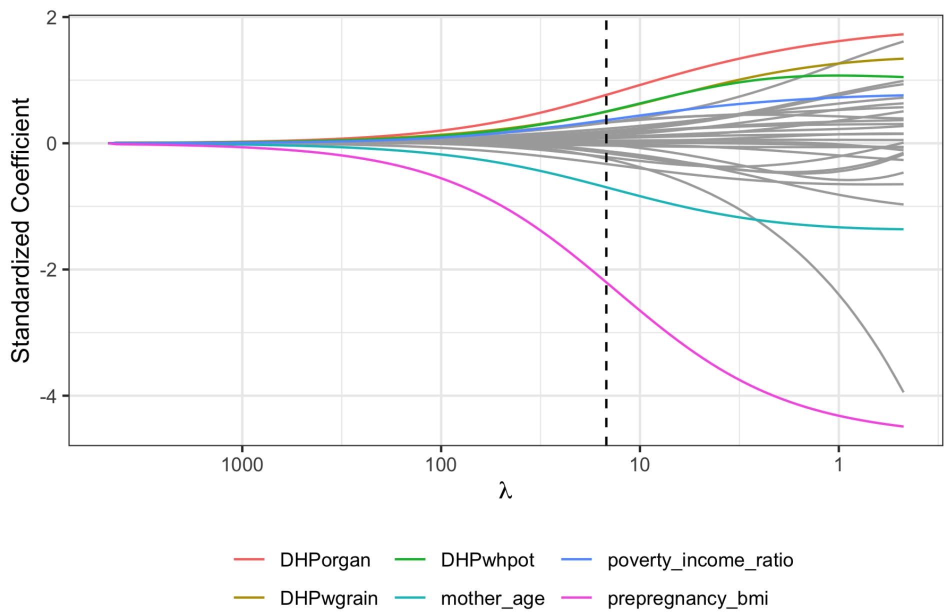
Ordinary Least Squares Regression

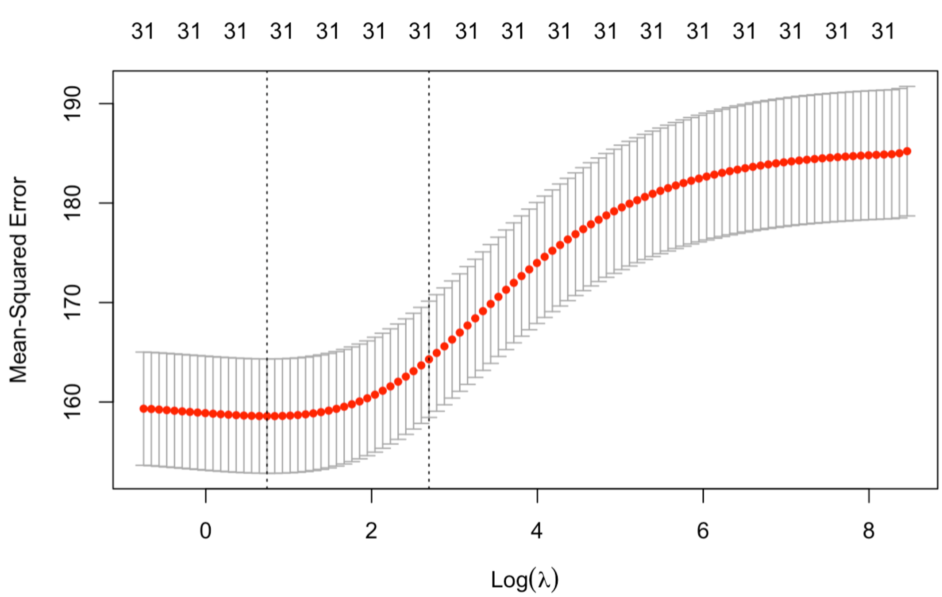
We first ran an ordinary least squares regression on all the data. The regression summary is included in the Appendix. The model had a multiple R-squared of 20.6%, indicating that 20.6% of variation in pregnancy weight gain can be explained by the features included in the model. The following features were significant at the 0.05 level: the number of ounces of lean meat consumed from organ meats, the updated folate intake, the mother's age, and the mother's pre-pregnancy BMI. The residuals do not appear to be skewed, based on the histogram below. Thus, we determined that we did not need to transform the data in order to run regression models. However, it is important to note that the residuals are fairly high, ranging from approximately -30 to 40, so more powerful predictive methods might be necessary.



Ridge Regression

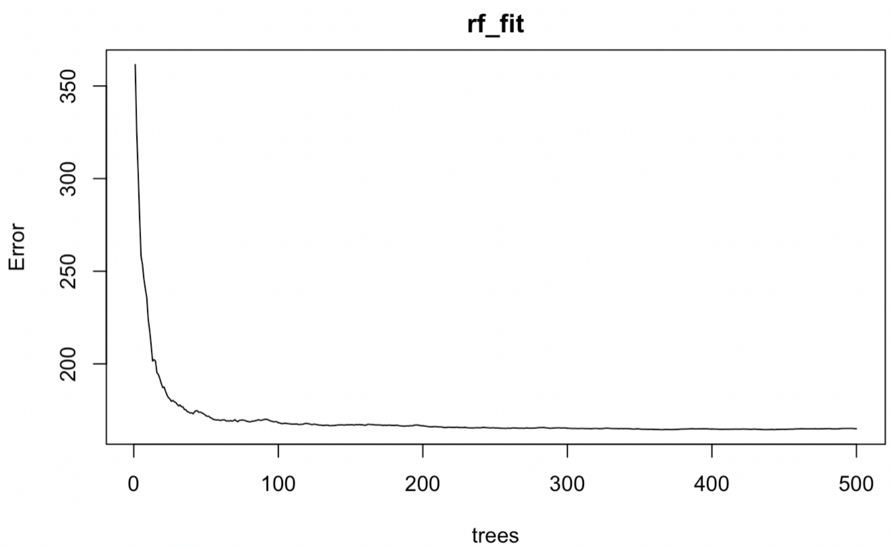
We then fit a ridge regression model to the data due to the fact that there are a large number of features, with only a few being significant in the linear regression model. Shrinkage in ridge regression helps diminish the insignificant features and emphasize the important ones. Thus, we thought the shrinking and penalization features of ridge regression might better predict trends in weight gain during pregnancy by giving the most important features more of an impact on our model, while reducing the impact of less important ones. We chose the optimal value for lambda according to the one-standard error-rule based on the cross-validation plot below. Based on the trace plot below, the top six most important features are the number of ounces of lean meat consumed from organ meats, the number of white potato servings consumed, the mother's poverty-income ratio, the number of whole grain servings consumed, the mother's age, and the mother's pre-pregnancy BMI.

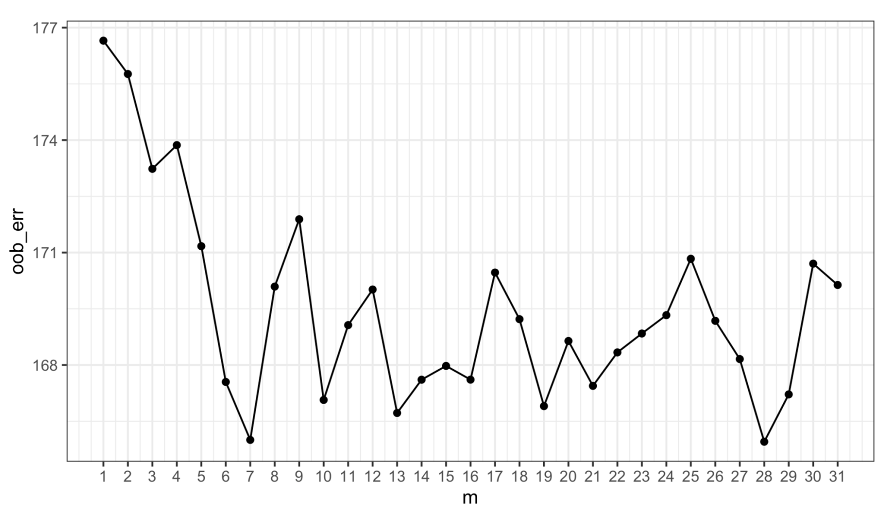




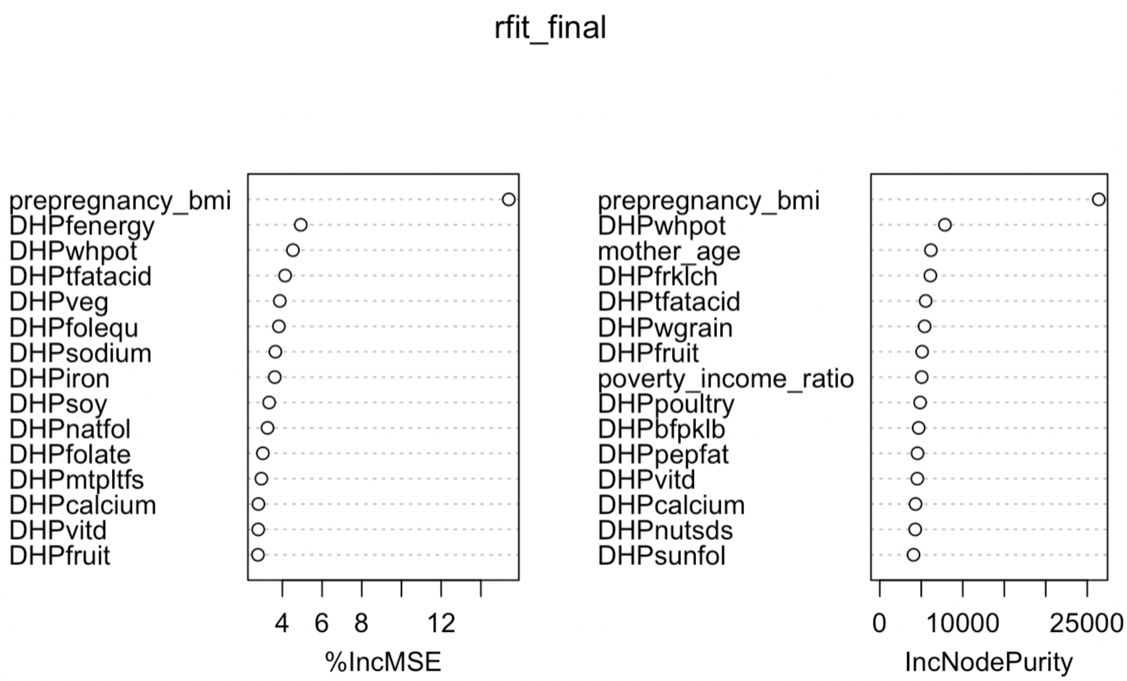
Random Forest

We fit a random forest model to the training data. We tuned the data for the optimal values of m, the number of features at each split, and B, the number of trees. We observed that the OOB error stabilizes for approximately B=100 fitted trees as depicted in the error versus trees plot below. Using the default model, m corresponds to the number of features divided by 3, which is 31/3 = 11 for our dataset. In order to determine the optimal value of m, we trained the model with B=100 trees on m values ranging from 1 to 31, where the upper bound of 31 would be equivalent to bagging. Based on the plot of OOB error versus m, we determined that the optimal value of m is 28.





Using the optimal values of m = 28 and B = 100 trees as determined above, we fit our random forest model and investigated variable importance for the top 15 variables, both purity-based and OOB. The former relates to the specific decrease in node impurities when a particular feature is used to split the data. The latter corresponds to the decrease in accuracy as a result of excluding the feature, since random scrambling assumes that no features have significant predictive power. The results can be seen below:



Based on the variable importance plots, the mother's pre-pregnancy BMI, the number of white potato servings consumed, and the total trans-fatty acids are among the top five highest variable importance using both measures, indicating that these particular features might be most relevant when predicting pregnancy weight gain. In particular, pre-pregnancy BMI appears to be the most important variable according to these measures.

Conclusions

Method Comparison

The following table includes the root mean squared errors for each of the models:

Model	Train RMSE	Test RMSE
Ordinary Least Squares Regression	12.12	12.53
Ridge Regression	12.66	12.27
Random Forest	5.16	11.95

According to the table, the random forest model has the lowest test error, followed by ridge. This makes sense because random forests aims to create decision trees that are individually closest to the most accurate prediction. Since random forests is a more powerful predictive method than OLS regression and ridge regression, it also has lower variance. As expected, ordinary least squares regression has the highest test error since it has the least predictive power. The training root mean squared error of the random forest model is less than half of the test root mean squared error, which could indicate overfitting. However, all test errors are relatively high, ranging from 11.95 to 12.53, indicating that the variables contained in the dataset might not be the most relevant predictors for weight gain during pregnancy.

The models identify similar variables as being important. All three models identify the pre-pregnancy BMI as being a significant predictor of weight gain during pregnancy. In particular, pre-pregnancy BMI is negatively associated with weight gain during pregnancy. The ordinary least squares regression and ridge regression also deem the number of ounces of lean meat consumed from organ meats and the mother's age to be important negative predictors of weight gain. Both ridge and random forest models also include the number of white potato servings consumed as an important positive feature in weight gain.

Takeaways and Recommendations

When looking at the results of all three models, we find that pre-pregnancy BMI is most strongly associated with pregnancy weight gain - their negative correlation infers that a lower pre-pregnancy BMI predicts more weight gain during pregnancy. As pre-pregnancy BMI has been a widely-studied risk factor for prenatal diet quality, the strong correlation between pre-pregnancy

BMI and pregnancy weight gain cements pregnancy weight gain as an important predictor for diet quality, and therefore infant health trajectories. Given that pregnancy weight gain is a more dynamic factor than BMI, our findings could possibly lend themselves to encouraging more studies to be done on pregnancy weight gain in lieu of BMI.

Taking a closer look at our random forests model, which was the model with the lowest test error, we can see that besides BMI, number of white potato servings and trans-fatty acid intake are among the other two variables that appear on both variable importance plots, which means that they probably have a strong impact on pregnancy weight gain. Since white potatoes are a form of carbohydrates that are high in starch, it does make sense that it has a high contribution to weight gain. Along the same vein, trans fatty acids are directly correlated with weight gain from well-supported research - eating too much could result in increase of LDL (low-density lipoprotein) cholesterol and risk in heart disease. In OLS regression and ridge regression, lean meat from organ meats did have a positive contribution to weight gain - however, interestingly enough, organ meat is incredibly nutritious and is a great source of folate and iron, both of which are variables in our dataset. That being said, it forces us to differentiate between good and bad weight gain. Weight gain has conventionally been attributed to deficient health, but in pregnancy, weight gain is almost essential for the average woman. Hence, we can conclude that white potatoes, trans fatty-acids, and organ meat do contribute the most to weight gain, but there is more nuance to the argument that it causes unhealthy weight gain.

To researchers that are interested in the contribution of pregnancy weight gain to prenatal diet quality, our final suggestion would be to research these three foods more closely and look at what health benefits they provide. For example, eating organ meat may lead to healthy weight gain, but eating too many trans fatty acids may lead to excess weight gain. It is important to analyze any health-related issues with context, and then make proper recommendations to pregnant women about their prenatal diets.

The socio-economic features that we included in our data set such as age and the poverty-income ratio appeared on one of our variable importance plots for random forests and our trace plot for ridge regression, but since there was no consistency among all three models, their relative contribution to weight gain during pregnancy is inconclusive for the scope of our analysis.

Limitations

Our first limitation within our dataset would be the disproportionate amount of energy and nutrient intake variables compared to socioeconomic and health related variables. We had 3 explanatory socioeconomic and health-related explanatory variables compared to the 28 energy and nutrient intake variables. Because of this disparity, our models predominantly had nutrient-focused features as the main contributors to weight gain. However, if we included more features related to socioeconomic status, such as race and income, or health, such as obesity history of the parents, we could have gotten more insight into the predisposition of increased pregnancy weight.

Another limitation to our dataset would be how the data was obtained. The data is directly sourced from a Diet History Questionnaire sent out as part of the Infant-Feeding Practices Study II, which means all of the values within this dataset are self-reported. Upon further inspection, the diet history questionnaire asks for a specific number, serving, or measurement for each food group, but rather gives the survey participant options to choose from.[6] Hence, the numbers within the data set are not exact measurements, but educated guesses inferred from the participants' responses. It may also suffer from response bias, where the participants lie about their intake of certain foods to appear healthier. Thus, the results of our analysis should be interpreted with caution due to underlying inconsistencies with actual data and data that was obtained via the questionnaire.

Our dataset also includes several explanatory variables that are highly correlated with each other. As mentioned before, we have several features that involve folate, such as folic acid, updated folate, and natural folate. Multicollinearity between these features may lead to high variance, or skew interpretability or relationships produced by the regression models we have.

Future Directions

We have concluded that pre-pregnancy BMI and pregnancy weight gain are highly correlated, so it would be beneficial to advance research about prenatal diet quality to explore the dynamic between pregnancy weight gain and its influence on infant health. Furthermore, as pregnancy weight gain is separate from normal weight gain, it would be best to first classify what a healthy weight gain is in terms of each woman, and then run the regression analyses again. For example, the same predictive models could be run on women with BMIs between 18.5-20. Because their BMIs are similar, their expected pregnancy weight gain would also be around the same, and we could more properly identify factors that cause excess weight gain by holding BMI relatively constant.

[6] Questionnaires: Breastfeeding and Infant Feeding Practices. (2021, August 10). Retrieved from https://www.cdc.gov/breastfeeding/data/ifps/questionnaires.htm

Appendix

Explanatory Variables

Listed below are the 31 explanatory variables that we used in our analysis. They can be split into two categories: socioeconomic and health related, and energy/nutrient intake. The words in parentheses are the column names in our clean dataset, followed by a short description of the feature.

Socioeconomic and Health-Related

- **Mother's Age** (mother_age): age of the mother when she gave birth
- **Poverty Income Ratio** (poverty_income_ratio): the ratio comparing poverty level with income; anything under 1.00 means that income is less than the poverty level, with larger numbers being more affluent families
- **Pre-pregnancy BMI** (prepregnancy_bmi): the mother's BMI before becoming pregnant

Nutrient/Energy Intake

- **Alcohol Intake** (DHPalcoholg): daily alcohol intake in grams of the mother during pregnancy
- **Dry Bean/Pea Intake** (DHPbeanpea): daily number of dry bean/pea servings that the mother has during pregnancy
- **Lean Meat from Beef/Pork/Lamb Intake** (DHPbfpklb): daily lean meat intake from beef/pork/lamb in ounces of the mother during pregnancy
- **Calcium Intake** (DHPcalcium): daily calcium intake in milligrams of the mother during pregnancy
- **Eicosapentaenoic Acid Intake** (DHPfat205): daily eicosapentaenoic acid intake, an omega-3 fatty acid with cardiovascular benefits, in grams of the mother during pregnancy
- **Docosahexaenoic Acid Intake** (DHPfat226): daily docosahexaenoic acid intake, an omega-3 fatty acid beneficial for the development of the infant brain, in grams of the mother during pregnancy
- **Calorie Intake** (DHPfenergy): daily calorie intake in kcal of the mother during pregnancy

- **Folate Intake** (DHPfolate): daily folate intake in mcg (micrograms) of the mother during pregnancy
- **Dietary Folate Equivalent Intake** (DHPfolequ): daily dietary folate equivalent intake in mcg of the mother during pregnancy
- **Lean Meat from Sausages/Luncheon Meat Intake** (DHPfrklch): daily lean meat intake from sausages/luncheon meat in ounces of the mother during pregnancy
- **Fruit Intake** (DHPfruit): daily number of fruit servings that the mother has during pregnancy
- **Iron Intake** (DHPiron): daily iron intake in milligrams the mother has during pregnancy
- **Lean Meat from Meat/Poultry/Fish Intake** (DHPmtpltfs): daily lean meat intake from meat, poultry, or fish in ounces of the mother during pregnancy
- **Natural Folate Intake** (DHPnatfol): daily natural folate intake (folate gained from foods) of the mother during pregnancy
- **Nuts/Seeds Intake** (DHPnutsds): daily nut or seed intake in ounces of the mother during pregnancy
- **Lean Meat from Organ Meat Intake** (DHPorgan): daily lean meat intake from organ meat in ounces of the mother during pregnancy
- **Percent Energy from Polyunsaturated Fats** (DHPpepfat): daily percentage of energy from polyunsaturated fats of the mother during pregnancy
- **Polyunsaturated Fats Intake** (DHPpfat): daily polyunsaturated fat intake in grams of the mother during pregnancy
- **Lean Meat from Poultry Intake** (DHPpoultry): daily lean meat intake from poultry in ounces of the mother during pregnancy
- **Sodium Intake** (DHPsodium): daily sodium intake in milligrams of the mother during pregnancy
- **Soy Intake** (DHPsoy): daily soy product intake in ounces of the mother during pregnancy
- Folic Acid Intake (DHPsunfol): daily folic acid intake in mcg of the mother during pregnancy
- **Trans-Fatty Acid Intake** (DHPtfatacid): daily trans-fatty acid intake in grams of the mother during pregnancy
- **Updated Folate Intake** (DHPupfol): daily updated folate intake in mcg of the mother during pregnancy
- **Vegetable Intake** (DHPveg): daily number of vegetable servings that the mother has during pregnancy

- **Vitamin D Intake** (DHPvitd): daily Vitamin D intake in mcg of the mother during pregnancy
- **Whole Grain Intake** (DHPwgrain): daily number of whole grain servings that the mother has during pregnancy
- **White Potato Intake** (DHPwhpot): daily number of white potato servings that the mother has during pregnancy

Linear Regression Summary

```
Call:
lm(formula = pregnancy_weight_gain ~ ., data = pdiet_train)

Residuals:
    Min      1Q  Median      3Q     Max 
-30.574  -8.949  -0.434   7.555  48.803 

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          5.571e+01  5.254e+00  10.602  < 2e-16 ***
DHPalcoholg          3.085e-02  2.863e-01   0.108 0.914220    
DHPbeanpea          -1.461e+00  3.596e+00  -0.406 0.684569    
DHPbfpklb           -3.959e-01  2.221e+00  -0.178 0.858530    
DHPcalcium           1.335e-03  2.398e-03   0.557 0.577916    
DHPfat205            1.955e+01  8.270e+01   0.236 0.813171    
DHPfat226            1.017e+01  2.696e+01   0.377 0.706057    
DHPfenergy           9.457e-04  2.342e-03   0.404 0.686490    
DHPfolate           -1.232e+01  1.399e+01  -0.881 0.378769    
DHPfolequ            1.005e+01  1.126e+01   0.892 0.372503    
DHPfrklch           -9.876e-01  2.147e+00  -0.460 0.645714    
DHPfruit             2.137e-01  2.297e-01   0.930 0.352588    
DHPiron              3.466e-01  3.607e-01   0.961 0.337006    
DHPmtpltfs           1.780e-01  2.203e+00   0.081 0.935606    
DHPnatfol            2.339e+00  3.241e+00   0.722 0.470617    
DHPnutsds            1.148e-01  1.407e+00   0.082 0.934959    
DHPorgan             8.481e+01  2.221e+01   3.818 0.000146 ***
DHPpepfat           -1.709e-01  6.349e-01  -0.269 0.787933    
DHPpfat              1.523e-01  2.738e-01   0.556 0.578118    
DHPpoultry           1.894e-01  2.020e+00   0.094 0.925297    
DHPsodium           -5.396e-04  1.504e-03  -0.359 0.719880    
DHPsoy               1.967e+00  2.544e+00   0.773 0.439580    
DHPsunfol           -4.705e+00  5.628e+00  -0.836 0.403457    
DHPtfatacid         -3.184e-01  4.174e-01  -0.763 0.445908    
DHPupfol            -9.776e-02  2.465e-02  -3.966 8.02e-05 ***
DHPveg               9.115e-01  5.161e-01   1.766 0.077769 .  
DHPvitd              4.395e-03  2.697e-01   0.016 0.987003    
DHPwgrain            1.508e+00  9.886e-01   1.525 0.127604    
DHPwhpot             1.459e+00  9.606e-01   1.518 0.129340    
mother_age          -2.238e-01  9.228e-02  -2.425 0.015528 *  
poverty_income_ratio 3.931e-01  2.496e-01   1.575 0.115691    
prepregnancy_bmi    -7.433e-01  7.283e-02 -10.206  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.37 on 750 degrees of freedom
Multiple R-squared:  0.206,	Adjusted R-squared:  0.1732 
F-statistic: 6.278 on 31 and 750 DF,  p-value: < 2.2e-16
```