



Tracing Trends in Macronutrient Intake and Energy Balance Across Demographics with Statistics and Machine Learning

Giovanni Pagano¹ and Weida Zhu²

Advisor: Michela Taufer

¹ Center for Bioinformatics and Computational Biology, University of Delaware, Newark, DE 19711

² Department of Electrical and Computer Engineering, University of Delaware, Newark, DE 19711

Motivations

- One of the most fundamental aspects of a healthy diet is intake of the three “macronutrients”—proteins, carbohydrates and fats
- A diet with too much or too little of any macronutrient can have a significant effect on short-term and long-term health
- Understanding how each of these macronutrients contribute to the total “energy balance” can allow people to correct deficiencies and customize their diet to their lifestyles
- Not everyone can identify or make changes—lack of nutrition education, insufficient financial resources to purchase higher-quality food, or a lack of access to healthcare
- People with low income or people with no college degree may be more more challenged to maintain a balanced diet

Our Key Question:

Can we predict possible macronutrient intake for an individual based on the available demographics information?

Our Approach

- How does nutrient and energy intake change over time? Is there a correlation between macronutrient intake and total energy intake?
- How does macronutrient intake vary across demographics like gender, age, race, education level and income level? Are education level and poverty level strong predictors of macronutrient intake?

Data of Interest: National Health and Nutrition Examination Survey

- Biannual survey of US children and adults to gauge diet and health status
- Combination of questionnaires, dietary recall and physical examinations
- 2013-2014: 10,175 total participants

Data Preprocessing

- Conversion of files to CSV format with tools provided by Michael Wyatt
- Focus on the demographic and dietary (day 1 intake) data files:
 - SEQN ID, Age, Education Level, Ratio of family income to poverty, nutrient and calorie intakes
- Filtering of dataset / removal of missing data
 - Focused on adults, people 20 and older as defined in NHANES
 - Removed people with no nutrient data

Statistical Testing to Determine Trends

- Unpaired two sample t-tests for equal means; equal variances assumed
- Correlation calculated for each nutrient versus caloric intake

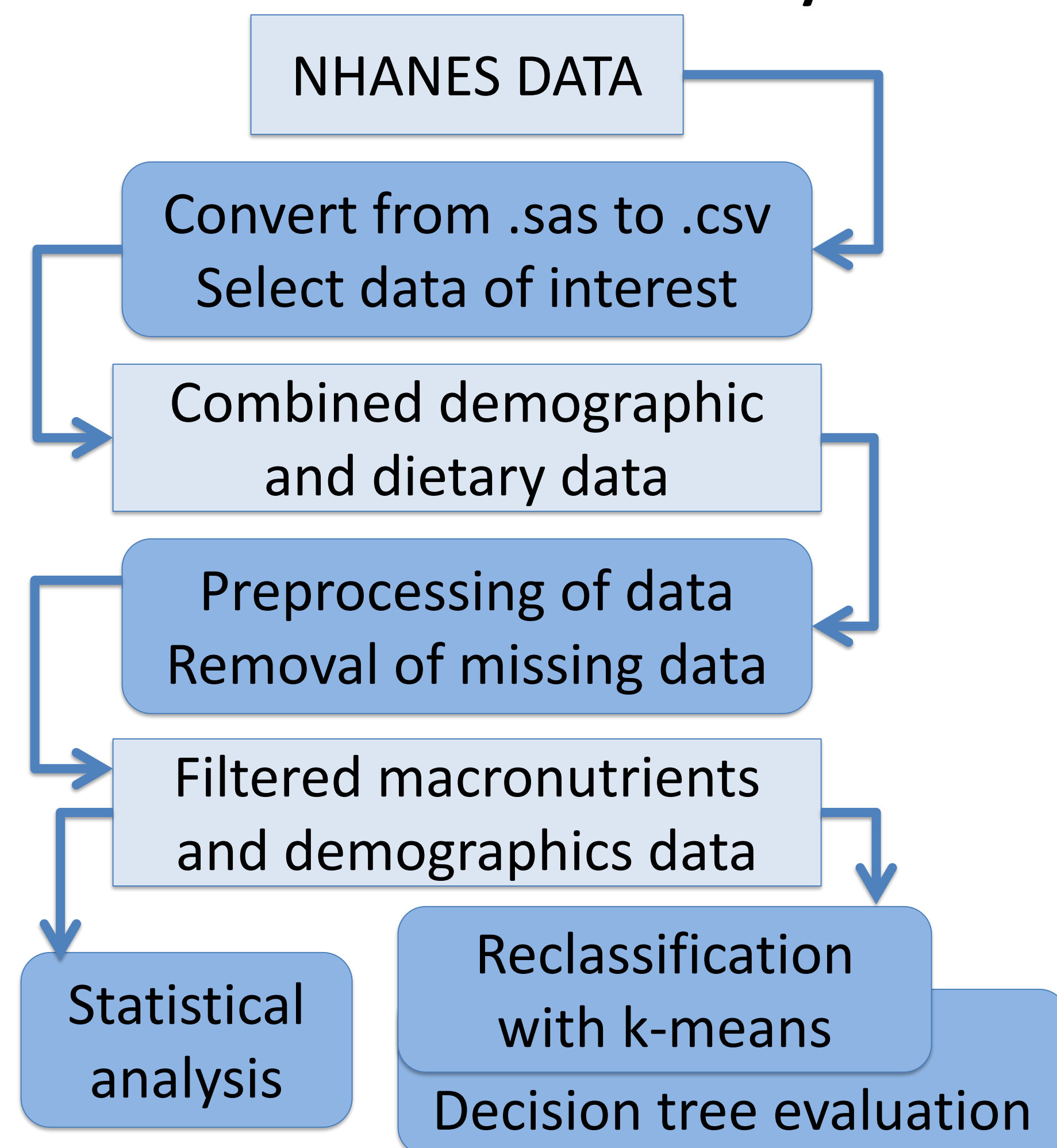
Reclassification of Demographic Data

- Simplify our testing for classification by converting continuous variables to categorical variables
- Used K-Means to establish boundaries—centroids used as cutoffs

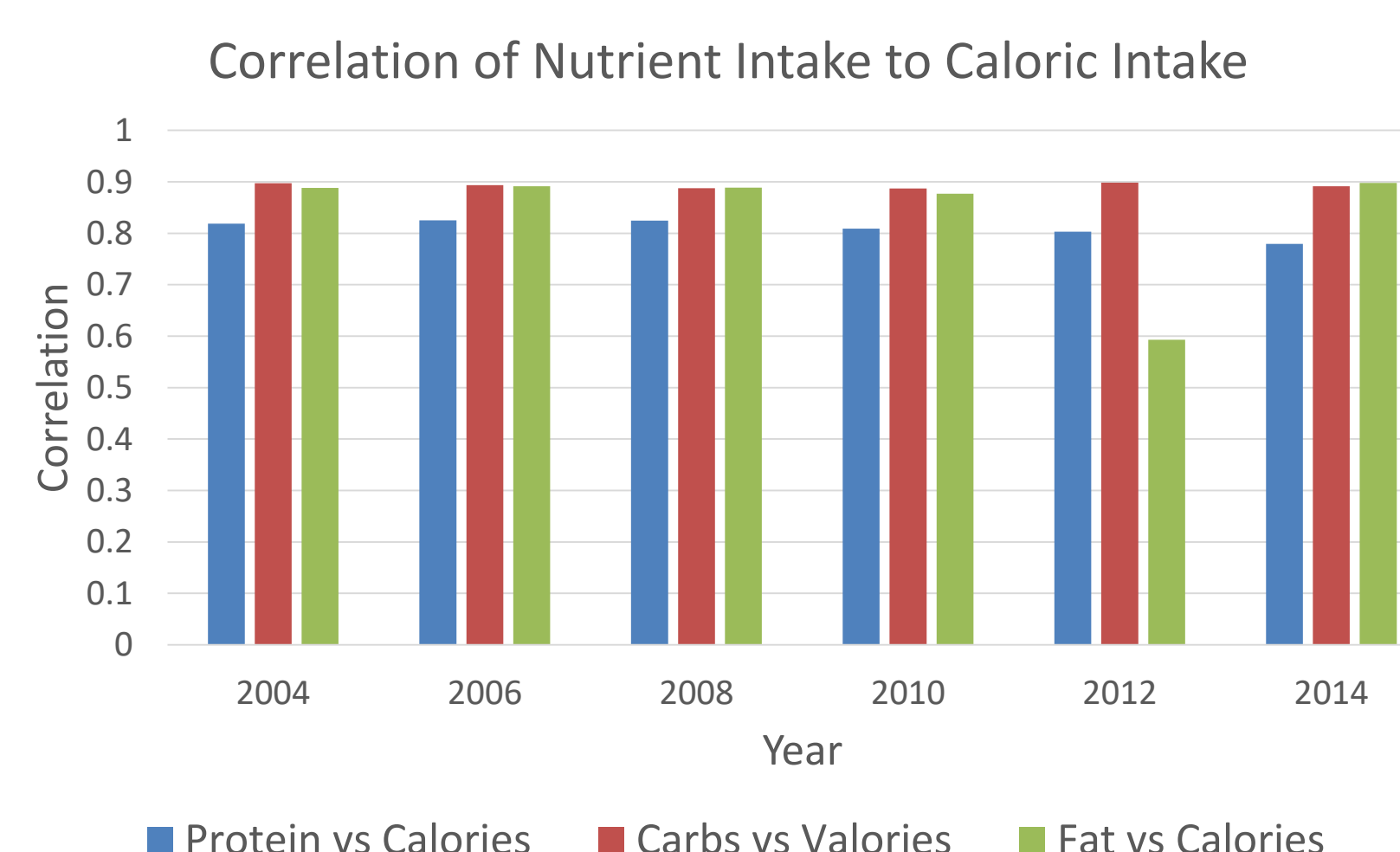
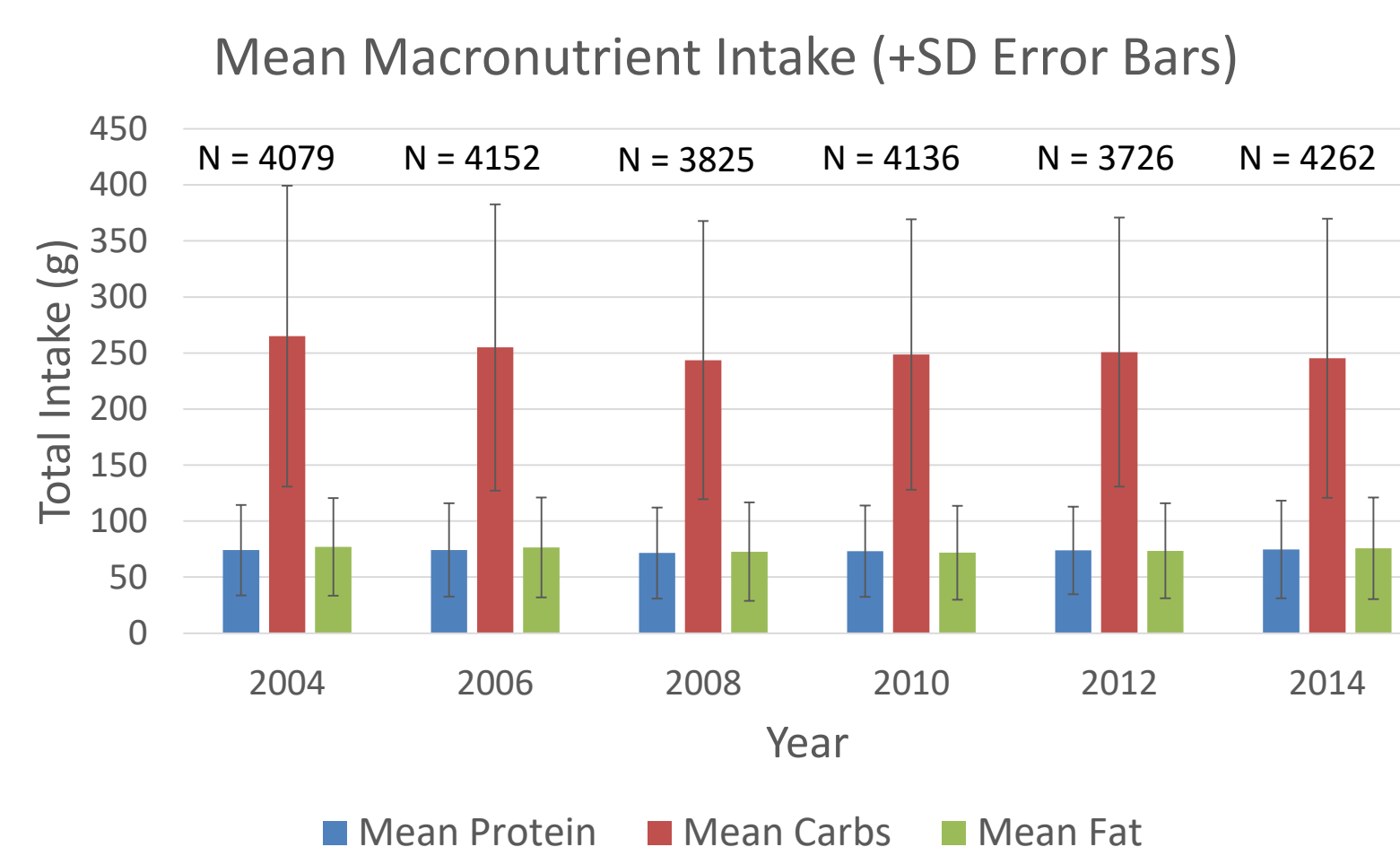
Classification with Decision Trees

- A set of rules to classify data, based on a given set of attributes for the data
 - Class: Macronutrient intake, three separate tests
 - Attributes: Education Level and Poverty Ratio
- Randomly divide the data into training and testing sets, use the training data to build the tree, and classify the testing data using the rules
- Error rate used to assess quality of trees

Workflow of the NHANES Analysis



Nutrient Intake from 2004-2014

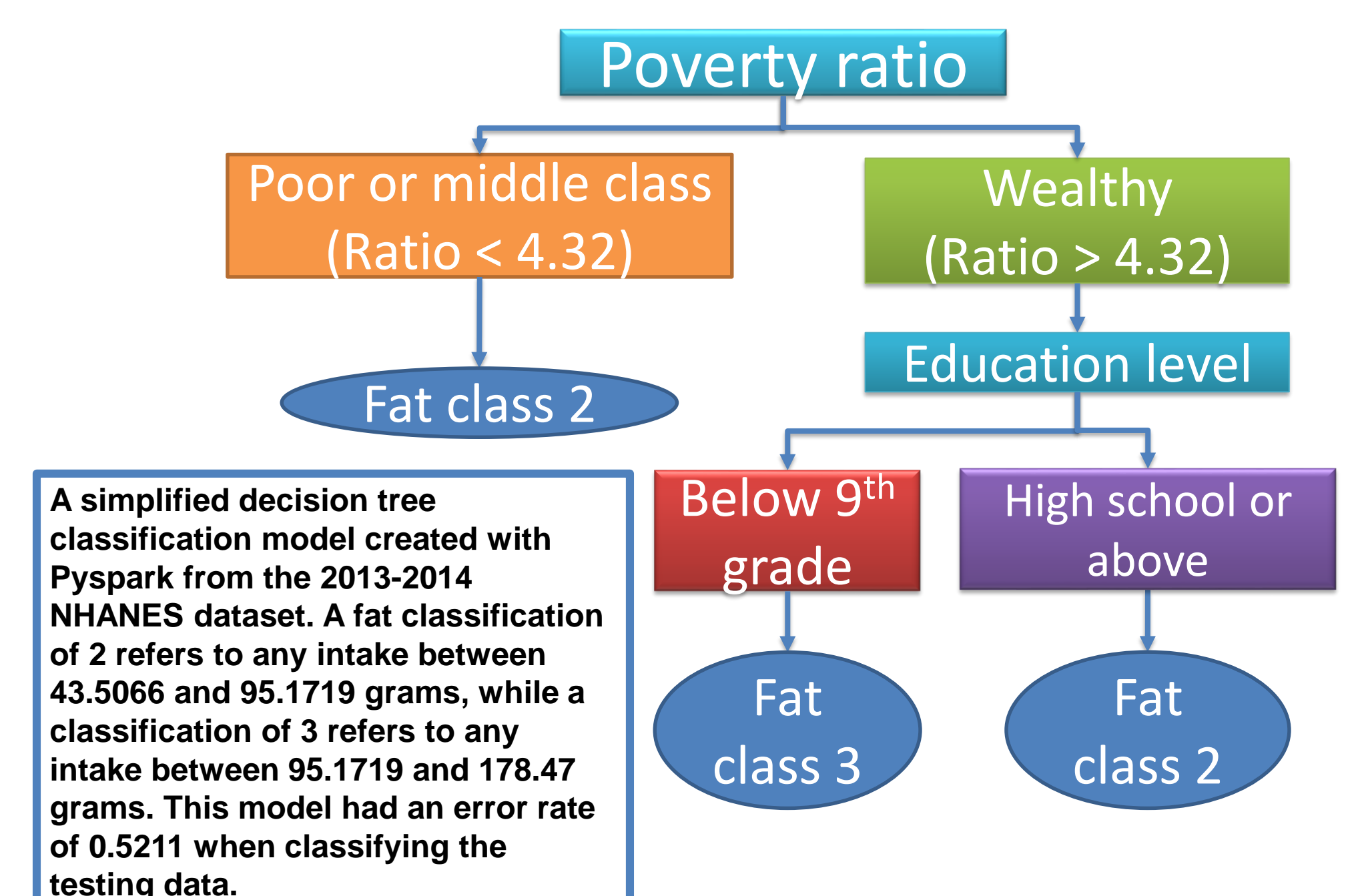


P-values for Equal Means T-Tests

	2004-2014	2006-2014	2008-2014	2010-2014	2012-2014
Protein	0.430553	0.540305	0.000502	0.072066	0.294181
Carbs	3.2E-12	0.000392	0.563143	0.205065	0.042073
Fat	0.177114	0.884844	0.788855	0.533601	0.595292
Calories	0.000176	0.096117	0.014295	0.174954	0.992877

Results of unpaired, two-sample t-tests for equal means ($p < 0.05$) of nutrient and caloric intakes. Boxes in yellow represent combinations of years where there is a statistically significant difference between the sample means.

Sample Decision Tree for Fat Intake



Results

- Some significant ($p < 0.05$) differences observed, but not consistent for each pair
- Strong positive correlation between carbohydrate and calories, fat and calories
- Prototype of decision tree algorithm has a very high error rate for all nutrients (~50% error)
- Key reasons for decision tree errors
 - We made some assumptions when merging some classes in education level may not reflect the reality of education and nutrition knowledge
 - We considered only education level and poverty ratio; these features may be only weakly correlated to nutrient and calorie intake

Future Work

- Explore the relationship between carbohydrate intake and energy intake in depth—where are the carbohydrates/fat coming from?
- Decision trees are still practical for this type of analysis, but more time is needed to improve the error rate
- Suggestions to improve decision tree accuracy:
 - Keep encoding for education level rather than combining it, and aim for a finer-grain classification scheme
 - Take additional or other features into consideration for decision tree; use methods such as lasso regression to determine which features are the most important, and incorporate into the decision tree