Latent class models for childhood obesity

Laura Antonucci
University of Foggia, Foggia, Italy – laura.antonucci @unifg.it

Corrado Crocetta
University of Foggia, Foggia, Italy – corrado.crocetta@unifg.it

Maria Gabriella Grassia
University Napoli, Federico II, Naples, Italy – mariagabriella.grassia@unina.it

Emma Zavarrone
University IULM, Milan, Italy – emma.zavarrone@iulm.it

Abstract

Using data about students from 6 to 10 years old, we want to identify the main causes of childhood obesity using some latent classes. We will try to see if the decisions, about the consumption of meat, eggs, pasta, cheese, salami, sweets, fruit, vegetable, fish and rice, allow to identify some life stiles that we can model as latent variables and that we can compare with some familiar behaviors such as daily consumption of sweets and snacks.

Keywords: childhood obesity, food choice, health, latent class models.

1. Introduction

In this paper we want to investigate causes of childhood obesity analysing the family decisions about consumption of meat, eggs, pasta, cheese, salami, sweet, fruit, vegetable, fish and rice.

It is well known that obesity is a major public health concern (Ogden, et al., 2010). Graversen (2014) asserts that the high preschool BMI is consistently associated with adult obesity, central obesity and early onset metabolic syndrome.

Avoidance of infant foods that provide excessive protein intakes, could contribute to a reduction in childhood obesity (Weber et al., 2014).

There are more than 42 million overweight children around the world. (Berger et al. 2014).

Childhood obesity can be brought on by genetics and environmental factors. The greatest risk factor for child obesity is the obesity of both parents. Some family behaviours can increase the risk of overweight. For example a decreasing number of children go outside and engage in active play as technologies, such as the television and video games, keep children indoors. Rather than walking or biking to a bus-stop or directly to school, more school-age children are driven to school by their parents, reducing physical activity. Advertising of unhealthy foods correlates with childhood obesity rates.

2. The research

Data comes from a research, sponsored by Fondazione IULM, Milano Ristorazione and Comune di Milano, involving psychologists, statisticians, food experts and nutritionist, about the diet of students attending primary schools in Milan metropolitan area.

He had 12,768 questionnaires from 119 public schools (coverage 81% of schools).

The questionnaire was filled in by parents of students (from 6 to 10 years old) and covered many areas such us:

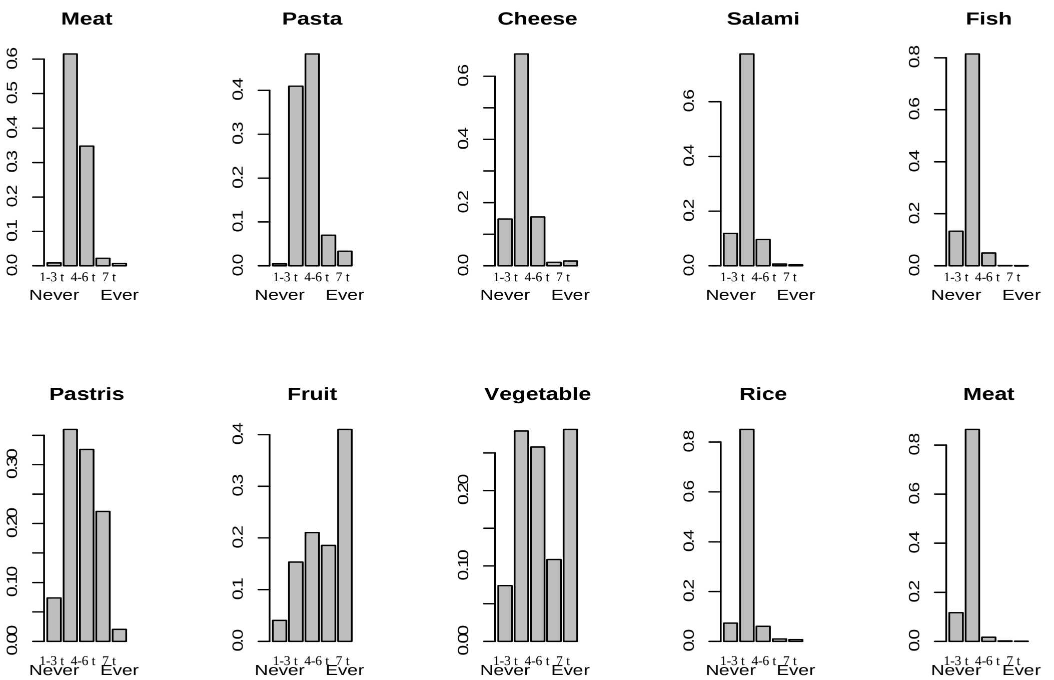
- parents and children identification data;
- education level of parents;
- parents and children food consumption habits;

- children anthropometric measures,
- physical activity frequency,
- TV watching habits.

In this paper we focus our attention on the weekly consumption habits of kids considering how many times a week they eat the following type of foods:

- pasta,
- rice,
- meat,
- sausages/salami,
- eggs,
- fish,
- cheese,
- fruits,
- vegetables,
- sweets and snacks.

Fig. 1 Histograms of weekly consumption of foods.



We can see by the histograms of the weekly consumption of food that some students never eat fish fruit and vegetables.

As said in the introduction, there is a relationship between parenting characteristics and adolescents' weight status. Obesity risk factors in children can be eating habits and weight perceptions.

Berge et al (2010) examined the relationship between the co-occurrence of various parenting characteristics and adolescents' weight status for population-based study of 4,746 diverse adolescents.

Huh et al. (2011) identify heterogeneous subgroups with respect to behavioral obesity risk factors in a sample of 4th grade children (*n* = 997) residing in Southern California. Multiple dimensions assessing physical activity, eating and sedentary behavior, and weight perceptions were explored.

Mazur et al. (2013) describe unique classes of weight-related health behaviors among college students. Latent class analysis was used to identify homogenous, mutually exclusive classes of nine health behaviors that represent multiple theoretically/clinically relevant dimensions of obesity risk among 2- versus 4-year college students using cross- sectional statewide surveillance data (*N* = 17,584).

In our study we want to verify if types of foods and family dinner behavior can contribute to obesity. For this reason we analyze a latent dimension "diet style" based on food consumption at home.

3. Latent class analysis

Latent class analysis (LCA) is a statistical technique for the analysis of multivariate categorical data based on multinomial distribution (Agresti 2002).
The underlying premise of LCA is that the responses to a set of observed variables are indicative of an underlying latent variable with a finite number of mutually exclusive classes or subtypes (Muthen & Muthen, 1998). Latent Class Analysis to determine empirically the diet style is a "categorical analogue" to factor analysis.
We estimated a latent class model using the 10 variables above described regarding the weekly food consumption habits to identify some latent classes:

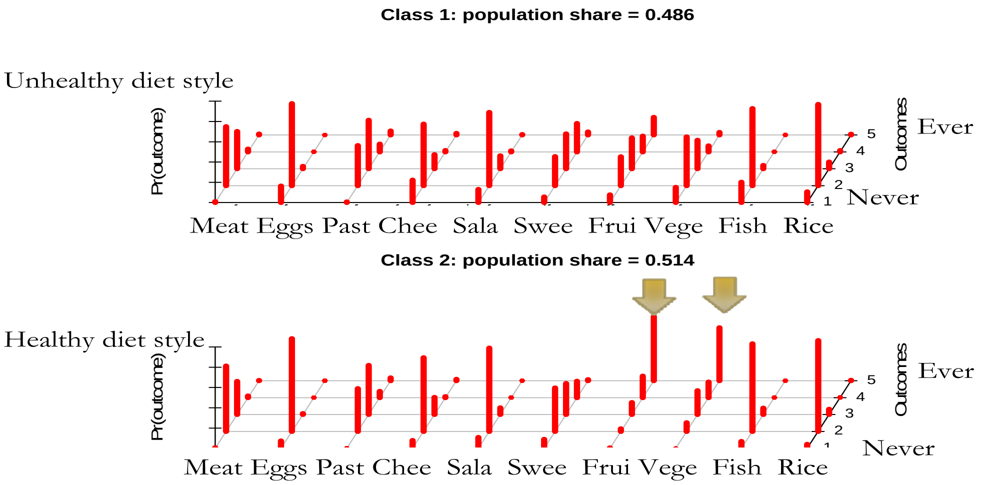
$$P\left(\mathbf{Y}_i = \mathbf{y} \mid X_i = x\right) = \sum_{l=1}^{n_x} \gamma_l(x) \prod_{m=1}^{M} \prod_{k=1}^{r_m} \rho_{mk|l}^{I(y_m=k)}$$

Where:

- **Y** is the matrix of 10 food consumption habits,
- **X** is the matrix of diet style.

We started with a simple model that considers 10 variables about weekly frequency of consumption of meat, eggs, pasta, cheese, salami, sweet, fruit, vegetable, fish and rice.

Fig. 2 Latent class model 1, weekly frequency of consumption with 2 latent classes



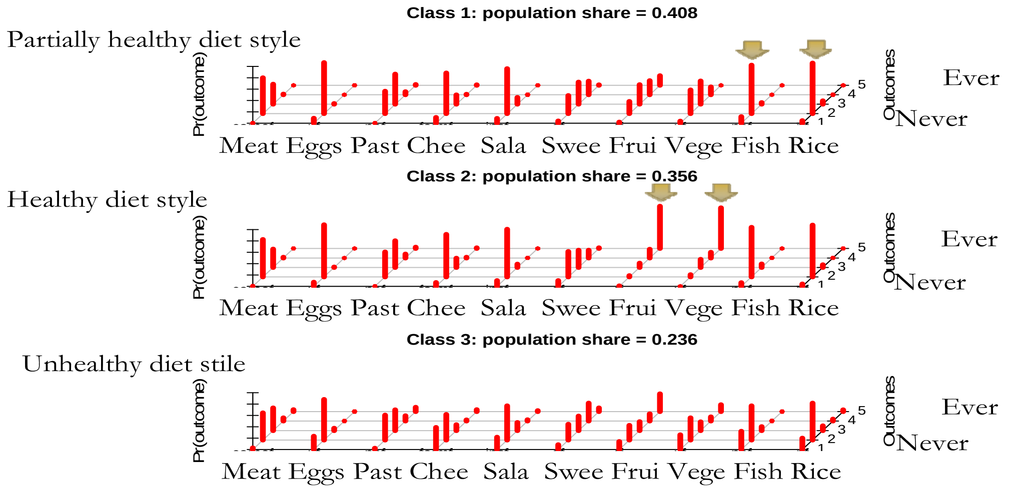
Latent Class Model n. 1: Weekly frequency of food consumption with 2 latent classes
Considering 12,768 observations, we first tried a model with 2 latent variables without covariates.
The goodness of fit criteria:
- Akaike information criterion (AIC)= 237.616
- Bayesian Information criterion (BIC)= 238.220
are quite good but, as we can see later, can be improved.
The predicted class memberships (by modal posterior distribution) is 48.7% for unhealthy diet stile and 51.3% for healthy diet style.

The estimated class population shares are similar to the predicted class memberships and show that the 48.0% of the respondent belongs to the first latent class of unhealthy diet stile and the 51.0% to the second class of healthy diet style.
Fig. 2 is very useful for the interpretation of the 2 components. The x axis considers the weekly consumption habits of 10 categories of foods. The second axis considers the frequency of consumption according the 5 classes never, 1-3 times a week, 4-6 times a week, 7 times a week and ever.
It is easy to see that in class 2 we have a strong consumption of healthy foods, such as fruit and vegetables, for this reason we decided to call the second class: healthy diet stile. On the contrary class 1 considers students are not used to eat healthy foods.

Latent Class Model n. 2: Weekly frequency of consumption with 3 latent classes for kids older then 7 years
Analyzing our data we found that students with less than 7 years are not free to choose their diet. For this we have focused our attention on the kids over 7 years old, considering only 7,638 observations.
For this second model the goodness of fit criteria are better then before:
- Akaike information criterion (AIC)= 142.884
- Bayesian Information criterion (BIC)= 143.730

The 3 predicted class memberships have: 44.9% of unhealthy diet stile, 34.6% of healthy diet style and 20.5% of partially healthy diet style. The estimated class population shares are similar to the predicted class membership, testifying that the model is stable and reliable, with 40.8% of unhealthy diet stile, 35.6% of healthy diet style and 23.6% of partially healthy diet style

Fig. 3 Latent Class Model n. 2: weekly frequency of consumption with 3 LC for kids older then 7 years.



As we can see in Fig. 3 the latent class 2 is characterized by the presence of numerous children who often eat fruits and vegetables, for this it has been indicated as healthy diet style. The class 1 is characterized by a consumption of 1 or 2 times a week of fish and rice and for this reason has been named partially healthy diet style. To the 3rd class belong the respondents that usually eat unhealthy foods.

Latent Class Regression Model n. 3: Weekly frequency of food consumption (with 3 LC) with respect to the number of daily snacks between meals.
To have more information we use as predictor the variable number of daily snacks between meals. Once again the model considers 7,638 observations (only kids over 7 years) and has goodness of fit criteria similar to model 2:
- Akaike information criterion (AIC)= 142.822

- Bayesian Information criterion (BIC)= 143.683.

Like for model 2 the predicted class memberships are: 44.6% for unhealthy diet stile, 35.9% for healthy diet style and 19.5% for partially healthy diet style. The same results we have for the estimated class population shares: 40.0% for unhealthy diet stile, 36.6% for healthy diet style and 23.4% for partially healthy diet style.

Tab. 1 Model 3 log ratio of the intercept and slope coefficients with p-values

Coefficients	Intercep	p-value	Slope	P-value
Log ratio 2/1	0.22	0.046	-0.18	0.000
Log ratio 3/1	-1.02	0.000	0.24	0.000

According to the results of Tab. 1 the log ratio prior probability that a respondent will belong to the healthy diet style with respect to the neutral group (of partially healthy diet stile) is:

$$Ln(p_{2i}/p_{1i})=0.22-0.18 \text{ x snack effect}$$

and the log ratio prior probability that a respondent will belong to the unhealthy diet style with respect to the neutral group (of partially healthy diet stile) is:

$$Ln(p_{3i}/p_{1i})=-1.02+0.24 \text{ x snack effect}$$

Fig. 4 Latent class regression model n. 3. Weekly frequency of consumption with 3 LC for kids older then 7 years with respect to snack effect.

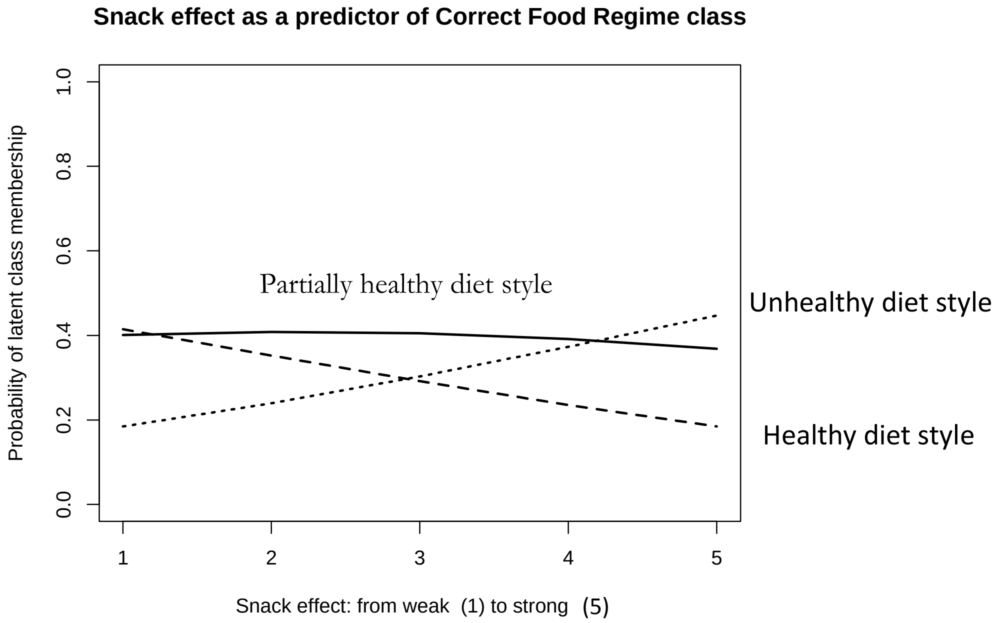


Figure 4 shows that the probability that a respondent belongs to the group of people with a healthy diet, decreases as the number of snacks for day increases. For this reason we can argue that students, that usually eat snacks, have a lower probability to be classified as healthy diet experts. On the other side the probability of being classified in the unhealthy diet stile group rises for those who declare that often eat snacks and sweets.

5. Conclusions

Many studies have found that high-calorie snacking is a major cause of childhood obesity. Chips, candy and other snack foods account for up to 27% of the daily caloric intake for children.
Researchers concluded that childhood snacking trends are moving toward three snacks per day. Childhood obesity has more than tripled in the past 30 years, putting children at risk for diabetes, heart disease and hypertension.
The eating behaviors are influenced by families and schools. The involvement of all of these actors will be needed to reverse the epidemic.
Schools can help students adopt and maintain healthy eating and physical activity behaviors. In the last decades major changes were made in the Italian school meal programs.
We hope this research can help to understand what is going on and to find strategies to hinder, childhood obesity.

References

Agresti A. 2002, Categorical Data Analysis, Hoboken: John Wiley& Sons.
Berger, Kathleen Stassen. 2014. *Invitation to the Life Span, Second Edition*. New York: Worth Publishers. p. 247. ISBN 1464172056.
Graversen L, Sørensen TIA, Petersen L, Sovio U, Kaakinen M, et al. (2014) Preschool Weight and Body Mass Index in Relation to Central Obesity and Metabolic Syndrome in Adulthood. PLoS ONE 9(3): e89986. doi:10.1371/journal.pone.0089986.
Huh, J., Riggs, N. R., Spruijt-Metz, D., Chou, C.-P., Huang, Z. and Pentz, M. (2011), Identifying Patterns of Eating and Physical Activity in Children: A Latent Class Analysis of Obesity Risk. Obesity, 19: 652–658. doi: 10.1038/oby.2010.228.
Mazur, A., Matusik, P., Revert, K., Nyankovskyy, S., Socha, P., Binkowska-Bury, M., …& Malecka-Tendera, E. (2013). Childhood obesity: knowledge, attitudes, and practices of European pediatric care providers. Pediatrics, 132(1), e100-e108.
Muthen LK, Muthen BO. *Mplus Users Guide*, 5th edn. Muthen & Muthen: Los Angeles, CA, 19981998.
Ogden, C.L., Carroll, M., Curtin, L., Lamb, M., Flegal, K. (2010). Prevalence of High Body Mass Index in US Children and Adolescents 2007-2008. Journal of American Medical Association, 303(3), 242-249.
Weber, Martina, et al. "Lower protein content in infant formula reduces BMI and obesity risk at school age: follow-up of a randomized trial." The American journal of clinical nutrition 99.5 (2014): 1041-1051.