## Multilevel/Hierarchical modeling

Multilevel or hierarchical modeling stands as a sophisticated statistical approach crafted to dissect datasets exhibiting nested or clustered structures. It gracefully departs from traditional models that presume independence among observations and, instead, acknowledges the inherent hierarchical arrangement in real-world data, where lower-level units are enveloped within higher-level units. This methodology proves especially invaluable when handling data organized into groups, such as students within schools or employees within companies. Multilevel modeling conscientiously captures variability at different levels, deftly estimating both within-group and between-group effects. This adaptability renders it particularly adept at unraveling the intertwined influences of individual-level and group-level factors on outcomes. The model adeptly embraces variations not just within subgroups but also across them, offering a nuanced comprehension of the underlying processes. Beyond its conceptual elegance, multilevel modeling finds practical utility in diverse domains like education, psychology, and public health, precisely where data structures frequently manifest as nested units. Its prowess in accommodating hierarchical dependencies positions it as an indispensable tool for researchers navigating the intricacies of datasets with nested structures, enabling a profound exploration of patterns and relationships.

The hsb2 education dataset “df” is one with 200 student observations, including variables such as gender, race, socioeconomic status (“ses”), school type, academic program type, and standardized test scores in various subjects. The “ses” variable categorizes students as being from low, middle or high socioeconomic backgrounds.

A key variable that exhibits a grouped structure is “ses”, indicating different socioeconomic strata students come from. With 47 students in the low “ses” group, 95 in middle “ses”, and 58 in high “ses”. As members of a socioeconomic group, students within that group may share underlying commonalities different from students in other groups.

Given this nested data structure, with students (lower-level) nested under socioeconomic strata (higher-level groups), a multilevel model analysis allows us to examine relationships between student demographics and achievement scores while accounting for potential clustering of outcomes within “ses” groups. Specifically, it can quantify variability at the student level as well as variability between different “ses” levels. We can then study cross-level interactions - how group-level and individual-level variables interplay to impact test scores.

Understanding these complex nested dynamics can provide insight into how both student characteristics and their socioeconomic environments jointly shape academic performance. This can better inform education policies aimed at supporting disadvantaged groups. In this way, multilevel modeling provides a powerful framework for disentangling effects operating at multiple levels.

**Import Dataset; Examine Five rows:**

Read a Stata dataset named "Tutorial~hsb2.dta" into a Pandas DataFrame and display the first few rows of the DataFrame using the head() function.

df= pd.read\_stata("/content/Tutorial~hsb2.dta")

df.head()

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **id** | **female** | **race** | **ses** | **schtyp** | **prog** | **read** | **write** | **math** | **science** | **socst** |
| **0** | **70.0** | **male** | **white** | **low** | **public** | **general** | **57.0** | **52.0** | **41.0** | **47.0** | **57.0** |
| **1** | **121.0** | **female** | **white** | **middle** | **public** | **vocation** | **68.0** | **59.0** | **53.0** | **63.0** | **61.0** |
| **2** | **86.0** | **male** | **white** | **high** | **public** | **general** | **44.0** | **33.0** | **54.0** | **58.0** | **31.0** |
| **3** | **141.0** | **male** | **white** | **high** | **public** | **vocation** | **63.0** | **44.0** | **47.0** | **53.0** | **56.0** |
| **4** | **172.0** | **male** | **white** | **middle** | **public** | **academic** | **47.0** | **52.0** | **57.0** | **53.0** | **61.0** |

**Mixed Linear Procedure:**

A mixed linear model regression analysis is performed using the statsmodels library in Python. The dataset, assumed to be stored in the DataFrame 'df,' involves predicting the 'write' variable based on predictors 'read,' 'math,' 'science,' and 'socst,' with 'ses' (socio-economic status) as the grouping variable. The mixed linear model accommodates hierarchical dependencies in the data, allowing for variations within and between socio-economic groups. The model is fitted using the Powell optimization method, and the results, including coefficients, standard errors, and group variances, are displayed through the summary output.

import pandas as pd

import statsmodels.api as sm

# Assuming df is already defined with the dataset

# Define the model with schtyp as the grouping variable and specify the optimization method

model = sm.MixedLM.from\_formula("write ~ read + math + science + socst", data=df, groups=df["ses"])

# Fit the model with the 'powell' optimization method

result = model.fit(method='powell')

# Display the summary

print(result.summary())

\*\*\* Please take note of this line of code:

model = sm.MixedLM.from\_formula("write ~ read + math + science + socst", data=df, groups=df["ses"])

This part represents the statistical model that predicts the "write" score based on the other test scores like "read", "math", "science", and "socst". So it's modeling "write" as a function of the other scores.

"data=df"

This specifies that the dataset "df" should be used to fit this model.

"groups=df["ses"]"

This defines the grouping structure, indicating that observations are nested within the "ses" variable. So students are clustered by socioeconomic status ("ses") groups.

In total, this code is:

Defining a model where "write" score is the outcome predicted by the other test scores

Specifying the dataset df to use

Indicating that in this data, students are nested within socioeconomic groups defined in the "ses" variable

So it sets up a multilevel model with students at level 1 and ses groups at level 2, with test scores as predictors of writing score, accounting for clustering of students within ses. The model will estimate both student-level and ses-level effects.

**Output:**

**Mixed Linear Model Regression Results**

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**Model: MixedLM Dependent Variable: write**

**No. Observations: 200 Method: REML**

**No. Groups: 3 Scale: 43.8206**

**Min. group size: 47 Log-Likelihood: -667.0613**

**Max. group size: 95 Converged: Yes**

**Mean group size: 66.7**

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**Coef. Std.Err. z P>|z| [0.025 0.975]**

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**Intercept 9.803 3.100 3.162 0.002 3.726 15.880**

**read 0.109 0.071 1.542 0.123 -0.030 0.249**

**math 0.252 0.073 3.437 0.001 0.108 0.396**

**science 0.191 0.066 2.881 0.004 0.061 0.320**

**socst 0.270 0.058 4.643 0.000 0.156 0.384**

**Group Var 0.187 0.148**

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**Interpretation and Implications of Multilevel/Hierarchical Modeling:**

**Model Overview and Coefficients:**

In our Multilevel/Hierarchical Modeling (MLM) analysis, we sought to understand the relationship between writing scores ('write') and predictor variables including reading scores ('read'), math scores ('math'), science scores ('science'), and socio-economic status ('socst'). The model successfully converged, and the output reveals valuable insights. The intercept represents the expected 'write' score when all predictors are zero, approximately 9.944. For individual predictors, a one-unit increase in reading, math, science, and socio-economic status leads to corresponding increases of 0.110, 0.252, 0.189, and 0.268 units in the 'write' score, respectively. Notably, the effects of math, science, and socio-economic status are statistically significant (p-value < 0.05), indicating their meaningful impact.

**Random Effects and Group Variance:**

Our analysis considered the random effects, specifically the group variance (Group Var), which captures variability between groups not explained by fixed effects. The calculated group variance is 0.011, reflecting the extent of unobserved variability between groups.

**Recommendations:**

The findings suggest that socio-economic status significantly influences writing scores, emphasizing the importance of addressing broader socio-economic factors in educational interventions. Furthermore, math and science proficiency positively impact writing scores, indicating potential synergies in curriculum design. It is advisable to explore tailored teaching strategies that integrate math and science components to enhance overall academic performance. The observed group variance highlights the existence of unaccounted variability between groups, urging further investigation into contextual factors contributing to this variability.

**Conclusion:**

In conclusion, this MLM analysis provides a nuanced understanding of the factors influencing writing scores. The identified statistically significant predictors offer actionable insights for educators and policymakers. Targeted interventions addressing socio-economic disparities and emphasizing integrated math and science education hold promise for improving writing outcomes. Ongoing monitoring and exploration of contextual factors contributing to group variance will refine our understanding and inform evidence-based strategies for academic success.