Detecting Inconsistent Data Types

Lukas Blass (1950003), Eunice Jun (1623594) & Sam Kaufman (1022827)

Motivation
All empirical fields rely on valid statistical analyses. Unfortunately, conducting valid statistical analyses is challenging. There are two interconnected challenges: picking the correct statistical test to test a hypothesis and applying the test to the appropriate data. Tea [2] aims to address the former challenge by automating test selection. However, Tea requires the data to be in long format, a common denormalized format. Tea only guarantees correct application of statistical tests to data when this assumption is met. Any errors made during data formatting ("wrangling") prior to use in Tea programs goes unnoticed. Tea's current inability to detect semantically incorrect data in long format threatens the validity of its analyses, which ultimately undermines its goal. This is a problem present in other tools, such as R and Python packages (e.g., statsmodels) that assume data to be formatted in specific ways.

As an example, consider an analyst's task of comparing the prices of cars across two different years. Suppose the dataset contains the following columns: Car model, Price in 1990 (as measured in dollars - e.g., 100,000), and Price in 2000 (as measured in a percentage change from the price in 1990- e.g., -10).

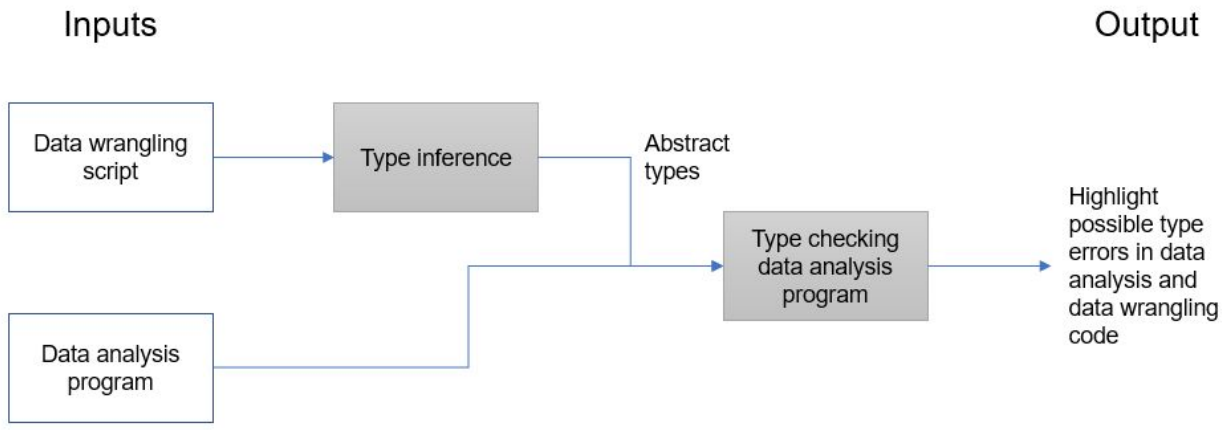
When the analyst reformats the dataset into long format, they collapse the two price columns into one and add a year column. The reformatted dataset now has the following columns: Car model, Price, and Year. However, the analyst forgot to change the units of the "Price in 2000." As a result, the resulting "Price" column has values of mixed units (implicit). All the values are still numbers, but they have semantically different meanings. Some refer to dollar prices. Others refer to percentages. In other words, data in the same column have incompatible *abstract types* [1].

Calling a statistical analysis function in R or Tea using the "Price" and "Year" columns still type checks and even executes, but the resulting analysis is invalid. The results are uninterpretable as the abstract types of data in the Price column are treated as dollar values, when they are really a mixture of dollar and percentage values.

Aim: We aim to surface potential errors in statistical analyses and data wrangling code to prevent inconsistent abstract types in data for the same variable/column.

Approach
We anticipate creating a linter for Python that could later be integrated into Tea. The linter would require two programs as input: 1) data wrangling code and 2) analysis code. As output, the linter would highlight lines of data wrangling and analysis code that are likely the source of error.

It operates in two steps on aforementioned inputs (data wrangling and data analysis programs). In a first step, abstract types of the columns of the input data are inferred using the data wrangling code. Every operation performed on the dataset reveals information about the types of the involved variables. For example, take the sum of two columns that provides us the information that both columns, as well as the result, must be of the same type. This process allows to refine the information about the types with every line of code. In the second step of the algorithm the knowledge about the abstract types is applied to the data analysis program and the user is alerted if inconsistencies with the inferred types are detected. This process is visualized in the diagram below.



A fundamental tension to this system design is found in the choice between the data wrangling or analysis code as the source of truth for the abstract type inference. We choose to infer abstract types from data wrangling code because we assume the wrangling code is more representative of users' intentions.

Given this problem, we pose the following research question and hypothesis:

Research question: How can using abstract types help analysts detect errors in statistical analysis and wrangling?
Hypothesis: Inferring abstract data types from data wrangling code will help analysts identify errors in statistical analysis and data wrangling more accurately and quickly than examining the wrangling and analysis code alone.

To scope our project, we propose to focus on data wrangling code that uses Pandas data frames to format/represent the data. Pandas is a commonly used library for data analysis [3]. While abstract type inference is a technique that already exists, we are unaware of any applications of the technique to the data science domain. We also focus on data analysis code that utilizes common Null Hypothesis Significance Testing.

Evaluation

We aim to evaluate our approach by conducting a user study. Our user study will involve a between-subjects study where half the participants try to detect errors in wrangling and analysis in Python scripts (from two corpora that Prof. Tim Althoff has) without using our linter and the other half use our linter. We will compare accuracy and time.

Integration with Tea

Our present focus is on Python scripts which wrangle data in Python and perform statistical tests using scipy, statsmodels, and other common libraries. We hope to explore integration with Tea if our approach proves promising.

References

[1] Guo,P., Perkins, J., McCamant, S., and Ernst, M. 2006. Dynamic inference of abstract types. In Proceedings of the 2006 international symposium on Software testing and analysis (ISSTA '06). ACM, New York, NY, USA, 255-265.

[2] Jun, E., Daum, M., Roesch, J., Chasins, S., Berger, E., Just, R., and Reinecke, K. (Under review) Tea: A High-level Language and Runtime System for Automating Statistical Analysis.

[3] Bobriakov, I. Top 15 Python Libraries for Data Science in 2017. https://medium.com/activewizards-machine-learning-company/top-15-python-libraries-for-data-science-in-in-2017-ab61b4f9b4a7