Exploring data subsets with vtree

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Abstract

Variable trees, a new method for the exploration of discrete multivariate data, allow exploration of nested subsets and calculation of corresponding percentages. These calculations can be laborious, especially when there are many multi-level factors and missing data. Here we introduce variable trees and their implementation in the vtree R package, draw comparisons with existing methods (contingency tables, mosaic plots, Venn/Euler diagrams, and UpSet), and illustrate their utility using two case studies. Variable trees can be used to (1) reveal patterns in nested subsets, (2) explore missing data, and (3) generate study-flow diagrams (e.g. CONSORT diagrams) directly from data frames, to support reproducible research and open science.

Keywords: Discrete, multivariate, visualization, tree, nested, subsets, R, CONSORT diagram, PRISMA diagram, study-flow diagram.

1. Introduction

Data exploration is a vital step to gain insights into data sets. Raw data needs to be cleaned, merged, summarized and assessed. This process is resource intensive, accounting for 80% of time spent on data analysis, by one estimate (Hellerstein et al. 2017). Furthermore, decisions made in this stage can impact scientific rigor and reproducibility. Recently, an appreciation has emerged for systematic and transparent protocols about data inspection steps to be performed prior to formal data analysis (e.g. Huebner et al. (2016)). Such protocols are designed to provide structure at this key stage while preventing statistical fishing for results.

Tools for data exploration, like tables and figures, have been historically important for science. For instance, in the late 1800s Florence Nightingale used rose plots to discover patterns in data that matched her clinical intuition—that most soldiers in the Crimean War were dying from hygiene-related infections rather than on the battlefield—and subsequently used this to influence the British Parliament (Nelson and Rafferty 2012). This and other methods were a catalyst for the early-1900’s revolution of statistical inference in many scientific fields.

Data exploration tools are more important today than ever. Data is more ubiquitous with a higher volume, velocity and variety than any time in history (Katal, Wazid, and Goudar 2013). Further, these data are more accessible to analysis due to cheaper and more powerful computation (Waldrop 2016). Consequently, data literacy and intuitive data exploration tools are required for exploring and communicating findings.

In this paper we introduce variable trees as a tool for exploring subsets of data, and their implementation in the vtree R package. The objectives of this paper are i) to compare variable
trees to several established data exploration tools, ii) to review the functionality of the vtree package, and iii) to demonstrate the utility of variable trees in two case studies.

Variable trees

Subsets play an important role in almost any data analysis. Consider the variables relating to the 2207 passengers and crew members of the Titanic, represented in the the data set titanic_data from the EIX R package (https://modeloriented.github.io/EIX/articles/titanic_data.html). Among other variables, the data set includes each person’s home country, which we have grouped into regions, and age, which we have divided into children (under age 13) and adults. In Figure 1 each person’s home region is shown, and within each region the number and percentage of children and adults are shown. Missing values are shown as NA.

![Variable tree for age nested within region of origin for people onboard the Titanic.](image)

Figure 1: Variable tree for age nested within region of origin for people onboard the Titanic.

We call this a variable tree. The vtree package provides a general solution for drawing variable trees and describing nested subsets.

Even in simple situations like Figure 1, it can be a chore to keep track of nested subsets and calculate the corresponding percentages. The denominator used to calculate percentages may also depend on whether the variables have any missing values, as discussed later. Finally, as the number of variables increases, the magnitude of the task balloons, because the number of nested subsets grows exponentially.

The structure of a variable tree

A variable tree consists of nodes connected by arrows. At the top of Figure 1, the root node of the tree contains all 2207 people on the Titanic. The rest of the nodes are arranged in successive layers, where each layer corresponds to a specific variable. This highlights one difference between variable trees and some other kinds of trees: each layer of a variable tree corresponds to just one variable. This is distinct from decision trees, where a layer may include splits based on different variables.

The nodes immediately below the root node in Figure 1 represent values of Region and are referred to as the children of the root node. Inside each of the nodes, the number of people is displayed and—for except for in a missing value node—the corresponding percentage is also shown. An example of a missing value node appears in Figure 1, where Region was missing (NA) for 81 people. Note that, by default, vtree displays “valid” percentages, i.e.

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1Since the Titanic example involves actual children, we need to be careful here with this technical use of the term “children”.

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the denominator used to calculate the percentage is the total number of non-missing values, in this case 2126. By default, vtree displays the full missing-value structure of the specified variables.

The final layer of the tree corresponds to values of Age. Each of these leaf nodes represents children and adults nested within a subset defined by a value of Region. Let's use the notation Region → Age to represent Age nested within Region.

A missing-value node, like any node, can have children. For example, of the 81 people for whom Region is missing, 10 were children and 71 were adults.

2. Methods of displaying discrete multivariate data

A variety of tools have been developed to display joint distributions of discrete variables, the most basic being the contingency table, often enhanced with row, column, or table percentages. For example, Table 1 presents the same information as Figure 1. Note that through the use of column percentages, the reader is encouraged to focus on age group nested within region.

|        | UK and Ireland  | Europe | North America | Other | NA |
|--------|-----------------|--------|---------------|-------|----|
| Child  | 36 (3%)         | 31 (9%)| 13 (4%)       | 19 (17%)| 10 (12%)|
| Adult  | 1320 (97%)      | 323 (91%)| 287 (96%)    | 95 (83%) | 71 (88%)|
| NA     | 0               | 2      | 0             | 0     | 0  |

Table 1: Contingency table for Region → Age for people on the Titanic. For each region, the marginal frequency and percentage is listed in italics. For each combination of region and age, the frequency and column percentage for age within each region is shown.

While the contingency table above is more compact than the variable tree in Figure 1, we find the variable tree to be more intuitive. Furthermore, domain experts often respond well to such visual representations.

Now suppose we’d like to examine Region → Age → Survived (i.e. survival within age within region of origin). Multi-way cross classifications (three or more variables) are typically displayed using several two-way tables, referred to as layers or slices. Table 2 shows two-way tables of survival within age group for each of the regions of origin. This is followed by a variable tree showing the same information (Figure 2).
### Table 2: Contingency table layers for Region → Age → Survived.
The name of each region is shown along with the marginal frequency and percentage (in *italics*), and underneath, the two-way contingency table for Age → Survived within that region. Along the top row of each table, frequency and percentage for age within that region is shown in *italics*. In each table, frequency and column percentage for survival within each age and region are shown.

#### UK and Ireland

|        | Adult     | Child | NA |
|--------|-----------|-------|----|
| Survived | 1320 (97%) | 36 (3%) | 0 |
| Did not survive | 973 (74%) | 19 (53%) | 0 |

#### North America

|        | Adult     | Child | NA |
|--------|-----------|-------|----|
| Survived | 287 (96%) | 13 (4%) | 0 |
| Did not survive | 160 (56%) | 7 (54%) | 0 |

#### Europe

|        | Adult     | Child | NA |
|--------|-----------|-------|----|
| Survived | 323 (91%) | 31 (9%) | 2 |
| Did not survive | 232 (72%) | 18 (58%) | 2 (100%) |

#### Other

|        | Adult     | Child | NA |
|--------|-----------|-------|----|
| Survived | 95 (83%) | 19 (17%) | 0 |
| Did not survive | 63 (66%) | 3 (16%) | 0 |

#### NA

|        | Adult     | Child | NA |
|--------|-----------|-------|----|
| Survived | 71 (88%) | 10 (12%) | 0 |
| Did not survive | 23 (32%) | 5 (50%) | 0 |
Figure 2: Variable tree for Region $\rightarrow$ Age $\rightarrow$ Survived with number and percent survival shown in each node. Table 2 shows the same information.

Note that by default, vtree shows percentages in each node except for the root. For example, of the 2207 people on board the Titanic, 300 (14%) were from North America, of whom 287 (96%) were adults, of whom 160 (56%) survived. In its simplest form, a contingency table only shows crosstabulated frequencies, corresponding to the frequencies shown in the leaf nodes of a variable tree. Additionally, a variety of marginal and conditional percentages are
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often shown.

As the number of variables increases, contingency tables for multi-way classifications become increasingly difficult to interpret. In such situations, large variable trees can also become unwieldy, however this can be mitigated by pruning away branches of lesser interest.

Contingency tables are not always more compact than variable trees. When most cells of a large contingency table are empty (in which case the table is said to be sparse), the corresponding variable tree may be much more compact since empty nodes are not shown. In the Titanic data set, there are two missing values of Age, and both are for individuals from Europe. This appears as a single node in Figure 2, but in Table 2 in addition to the cell showing these 2 missing values, there are 9 cells containing zero.

Like contingency tables, variable trees show numerical values (frequencies and percentages) rather than using graphical elements such as area to encode such quantities. In contrast to contingency tables, which use a tabular layout to represent subsets, variable trees use the graphical arrangement of nodes and arrows to represent the nesting structure.

Visualization of discrete multivariate data

Several visualization methods have been proposed for discrete multivariate data. Barplots are often used to visually represent the number of observations of each value of a variable. They can also be produced for subsets, defined by values of another variable. A more compact representation is the stacked barplot, however these are harder to read since they there is no common baseline, except for the bottom category in the stack.

An elegant extension of the stacked barplot is the mosaic plot (Hartigan and Kleiner 1981). In a mosaic plot, the area of each rectangle represents the number of observations in the corresponding subset of the data. Mosaic plots are available in base R through the mosaicplot function, or via the ggmosaic package or the vcd package. Mosaic plots can provide an intuitive visual representation of the number of observations in subsets of the data, however they tend to become overwhelming when there are more than three variables. Figure 3 is a mosaic plot for Region → Age → Survived for the people onboard the Titanic, as in Table 2 and Figure 2.
Figure 3: Mosaic plot for Region $\rightarrow$ Age $\rightarrow$ Survived for people on the Titanic. Each rectangle corresponds to a subset of the data and the area of the rectangle represents the relative frequency. Table 2 and Figure 2 show the same information.

Visualizations like Figure 3 have advantages and disadvantages compared to text and tabular summaries. On the one hand, they represent quantitative and qualitative information in a way that is quickly decoded by our visual perceptual systems. On the other, visualizations can be unfamiliar and even perplexing compared to the familiarity of numerical and tabular representations. On a practical level, text and tabular information are easier to format and manipulate with current software. Variable trees have characteristics (and hence advantages as well as disadvantages) of both tabular representations and visualizations,
Data representing set membership

A special type of discrete multivariate data is when all of the variables are binary, in which case they can be interpreted as representing set membership. Venn diagrams use overlapping closed curves such that all intersections between sets are represented by overlapping areas. Euler diagrams are like Venn diagrams but empty intersections need not be shown. Venn and Euler diagrams have long been used to represent the intersection of sets. For datasets, software is available to calculate the number of observations in each of the intersections, for example in R, the VennDiagram and venneuler packages. A further elaboration of these diagrams is to make the areas of the sets and their intersections approximately proportional to the number of observations in each subset. The package eulerr provides this functionality. For example, in Figure 4 a dataset of Wilkinson (2012) is represented using an approximately area-proportional Euler diagram. As the number of sets grows, Venn and Euler diagrams can become unwieldy.

Figure 4: Euler plot for the dataset of Wilkinson (2012).

An innovative way to represent the intersections of a large number of sets is UpSet (Lex et al. 2014). The R package UpSetR (Conway, Lex, and Gehlenborg 2017) was used to produce Figure 5 for the dataset of Wilkinson (2012). UpSet uses a grid layout to represent the intersections (see the dots at the bottom of Figure 5), together with bar graphs on each side to represent the size of sets and intersections.
Variable trees can also represent the intersection of sets, however unlike UpSet and area-proportional Euler diagrams, they do not use graphical elements to encode quantity. Like non-proportional Venn Diagrams, variable trees graphically depict the relationships between subsets of the data, but represent quantities numerically (Figure 6). Unlike Venn, Euler, and UpSet diagrams, variable trees require a prespecified ordering. For example, Figure 6 uses the ordering $A \rightarrow B \rightarrow C \rightarrow D \rightarrow E \rightarrow F$. 
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Figure 6: A variable tree for the dataset of Wilkinson (2012).

vtree can also display a pattern tree, which depicts every intersection. Each row in Figure 7 corresponds to the combination of values represented by a terminal node in Figure 6. Since the intermediate nodes in Figure 6 are not represented, this is a loss of information. The pattern tree is much easier to read, however. Pattern trees have some of the same structure as an UpSet plot, except that sizes of subsets are not represented graphically as in the bar graphs on the sides of an UpSet plot.

Figure 7: A pattern tree for the dataset of Wilkinson (2012).
3. Package functionality

This section provides an overview of the features of the **vtree** package. Additional resources are available in the package vignette, a cheatsheet, and video tutorials on YouTube.

**Calling vtree**

Suppose the Titanic data are in a data frame called `td`. To display a variable tree for a single variable, say `Class`, use the following command:

```r
R> vtree(td, "Class")
```

![Figure 8: A simple variable tree.](image)

The variable `Class` is specified as a character string. To produce a variable tree for `Class → Age`, the character string is specified as "Class Age":

```r
R> vtree(td, "Class Age", horiz=FALSE)
```

![Figure 9: A two-layer vertical variable tree.](image)

By default, `vtree` produces horizontal trees. The tree in Figure 9 is vertical because of the specification `horiz=FALSE`.

**Pruning**

When a variable tree gets too big, or you are only interested in certain parts of the tree, it may be useful to remove some nodes along with their descendants. This is known as *pruning*. For convenience, there are several different ways to prune a tree, described below.

Suppose you don’t wish to show the “Europe” node or the “Other” node (which represents people from other parts of the world such as India, the Middle East, etc.). Specifying `prune=list(Region=c("Europe","Other"))` removes those nodes, and all of their descendants:
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R> vtree(td,"Region Age", prune = list(Region = c("Europe", "Other")),
+     horiz = FALSE)

R> vtree(td,"Region Class gender Age",
+     keep = list(Region = "Europe", Class = "3rd", gender = "male"))
number of missing values. On the other hand, here’s what happens when \( \text{vp}=\text{FALSE} \):

\[
\text{R} > \text{vtree(td, "Region Class gender Age",}
+ \quad \text{keep = list(Region = "Europe", Class = "3rd", gender = "male"), vp = FALSE)}
\]

![Diagram of vtree output with missing value node removed](image1)

Figure 12: Using the keep parameter with \( \text{vp} \) set to \( \text{FALSE} \).

Note that the missing value node for \text{Region} is no longer present, since the percentage for the “Europe” node can be interpreted without knowing how many missing values are present. Also, note that missing value node for \text{Age} includes a percentage, and the percentages for the other nodes of \text{Age} are slightly different. (With only two missing values, the difference is slight, but as the proportion of missing data increases, the percentages become substantially different.)

An alternative is to prune \text{below} the specified nodes (i.e. to prune their descendants), so that the counts always add up. In the present example, this means that the other nodes will be shown, but not their descendants. The \text{prunebelow} parameter is used to do this:

\[
\text{R} > \text{vtree(td, "Region Age",}
+ \quad \text{prunebelow = list(Region =c("UK and Ireland", "North America", "Other")))}
\]

![Diagram of vtree output with prunebelow parameter](image2)

Figure 13: Using the prunebelow parameter.

The complement of the \text{prunebelow} parameter is the \text{follow} parameter. Instead of specifying which nodes should be pruned below, this allows you to specify which nodes should be followed.
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(that is, not pruned below).

As a variable trees grow, it can become difficult to see the forest for the tree. For example, the following variable tree is hard to read.

```r
R> vtree(td, "Class Region", horiz = FALSE)
```

![Variable tree](attachment:variable_tree.png)

**Figure 14:** A variable tree that is hard to read.

One solution is to prune nodes that contain small numbers of observations. For example if you want to only see nodes with at least 50 observations, you can specify `prunesmaller=50`, as in this example:

```r
R> vtree(td, "Class Region", horiz = FALSE, prunesmaller = 50)
```

![Variable tree](attachment:variable_tree_pruned.png)

**Figure 15:** Using the `prunesmaller` parameter.

Similar to the `keep` parameter, when valid percentages are used (`vp=TRUE`, which is the default), nodes represent missing values will not be pruned. As noted previously, this is because percentages are confusing when missing values are not shown. On the other hand, when `vp=FALSE`, missing nodes can be pruned.

**Labels for variables and nodes**

Readability of a variable tree can be improved by customizing the variable and node names using the `labelvar` and `labelnode` parameters. By default, `vtree` labels variables and nodes exactly as they appear in the data frame. But it is often useful to change these labels.

For example, the `embarked` variable indicates the port where a passenger or crew member went on board the Titanic. Suppose we wish this variable to appear as `Port` in the variable tree. The `labelvar` parameter is used to do this.
By default, `vtree` labels nodes (except for the root node) using the values of the variable in question. (If the variable is a factor, the levels of the factor are used). Sometimes it is convenient to instead specify custom labels for nodes. The `labelnode` argument can be used to relabel the values. For example, to relabel the classes as “First Class”, “Second Class”, and “Third Class”:

```r
R> vtree(td,"Class", horiz = FALSE, labelnode = list(Class = c("
+ "First Class" = "1st", "Second Class" = "2nd", "Third Class" = "3rd")))
```

**Figure 16: Using the labelvar parameter.**

**Figure 17: Using the labelnode parameter.**

**Specification of variables**

For convenience, in the call to the `vtree` function, you can specify variable names (separated by whitespace) in a single character string. (If, however, any of the variable names have internal spaces, the variable names must be specified as a vector of character strings.) Additionally, several modifiers can be used, as detailed below.

If an individual variable name is preceded by `is.na:`, that variable will be replaced by a
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missing value indicator in the variable tree. This facilitates exploration of missing data, for example:

R> vtree(td, "Class is.na:fare", horiz = FALSE)

A variety of other specifications are available. For example <, =, and > can be used to dichotomize numeric variables. While this is a powerful tool for data exploration, a word of caution is needed. To ensure scientific rigor, it is essential that this functionality not be used to explore a variety of dichotomizations of a predictor variable in relation to the outcome variable. There is a large literature on the misuse of dichotomization and its detrimental effect on statistical inference (Altman 1994). It is therefore recommended that any dichotomization using vtree be conducted according to a pre-specified protocol (Huebner et al. 2016).

R> vtree(td, "Class sibsp>2", horiz = FALSE)

Displaying summary statistics in nodes

It is often useful to display information about other variables (apart from those that define the tree) in the nodes of a variable tree. This is particularly useful for numeric variables, which generally would not be used to build the tree since they have too many distinct values. The summary parameter allows you to show information (for example, the mean of a numeric variable) within each subset of the data frame.

Suppose you are interested in summary information concerning the number of siblings/spouses aboard the Titanic (the sibsp variable) for all of the observations in the data frame (i.e. in the root node). In that case you don’t need to specify any variables for the tree itself:
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Figure 20: Using the summary parameter for the entire data frame.

Suppose you wish to see the mean of this variable within levels of Region and Class. (To reduce the size of this tree we’ll hide the crew and the “Other” region.)

```
R> vtree(td, "Region Class", summary = "sibsp \mean \%mean\%", horiz = FALSE, +    prune = list(Region = "Other", Class = "Crew"))
```

Figure 21: Using the summary parameter to produce customized summaries.

The \%mean\% code is one of several summary codes. Summary codes always start and end with \%. A list is shown in Table 3.

| summary code | variant | result |
|--------------|---------|--------|
| \%mean\%     | \%meanx\%* | mean   |
| \%SD\%       | \%SDx\%*  | standard deviation |
| \%sum\%      | \%sumx\%* | sum    |
| \%min\%      | \%minx\%* | minimum |
| \%max\%      | \%maxxx\%* | maximum |
| \%range\%    | \%rangex\%* | range   |
| \%median\%   | \%medianx\%* | median |
| \%IQR\%      | \%IQRx\%* | interquartile range |
| \%freq\%     | \%freq_\%** | frequency of values of a variable |
| \%npct\%     |          | frequency and percentage |
| \%pct\%      |          | same as \%npct\% but percentage only |
| \%list\%     | \%list_\%** | list of individual values, separated by commas |

*Missing values are suppressed. Caution is recommended.
**shows each value on a separate line.

Table 3: Summary codes.

Sometimes, you might want to only show summary information in particular nodes. Table 4...
lists codes to control where summary information is shown.

| code             | summary information restricted to                  |
|------------------|-----------------------------------------------------|
| %noroot%         | all nodes except the root                           |
| %leafonly%       | leaf nodes                                          |
| %var=v%          | nodes of variable v                                 |
| %node=n%         | nodes named n                                       |

Table 4: Control codes.

Pattern trees

Each node in a variable tree provides the frequency of a particular combination of values of the variables. The leaf nodes represent the observed combinations of values of all of the variables. For example, in a variable tree gender nested within Class, the leaf nodes correspond to Male and Female. These combinations, or patterns, can be treated as an additional variable. And if this new pattern variable is used as the first variable in a tree, then the branches of the tree will be simplified: each branch will represent a unique pattern, with no sub-branches. A pattern tree can be easily produced by specifying pattern=TRUE. For example:

```
R> vtree(td, "Class gender", horiz = FALSE, pattern = TRUE)
```

![Pattern tree diagram](image)

Figure 22: A pattern tree.

A special pattern tree can be used to show missing values with the check.is.na parameter:
4. Case Study: A study-flow diagram

Study-flow diagrams provide a visual representation of how participants (or study units) meet or do not meet a sequence of inclusion criteria. These diagrams provide critical information to the reader of published study. Medical research in particular has embraced these data visualizations as part of recommended reporting guidelines. Randomized clinical trials use CONSORT diagrams to show the flow of participants through a single study (Schulz, Altman, and Moher 2010). Systematic reviews use PRISMA flow diagrams to depict study screening (Page et al. 2020), (Stovold et al. 2014). While presenting study-flow diagrams is widely considered to be best practice, preparing these diagrams has traditionally been a slow, resource-intensive, manual process, which has to be repeated when small changes are made to the data.

\texttt{vtree} uses an R data frame to make a data-driven study flow diagram. This automates the production of study-flow diagrams. As more data arrives, data cleaning changes the existing data and the analysis plan is modified after initial assessment of the data (Huebner et al. 2016), the study-flow diagram is easily kept up to date. Not only does this increase efficiency, it minimizes the risk of introducing human error.

Consider, for example, the Remdesivir trial of Spinner et al. (2020), in which 612 patients with confirmed severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection and moderate COVID-19 pneumonia were screened for inclusion. Although, in this case, the full data set is not publicly available, the variables required for the flow diagram can be reconstructed from Figure 1 of the published paper. The \texttt{build.data.frame} function built into the \texttt{vtree} package makes it easy to construct a data frame indicating which participants were screened, included (and of these, who was eligible, and who consented), the group participants were randomized to, and who started the intervention. (Additional details have been omitted for the sake of brevity.)
R> rem <- build.data.frame(
+   c(  "included","elig","consent","randgrp","started"),
+   list(0, 0, 1, 0, 0, 13),
+   list(0, 1, 0, 0, 0, 3),
+   list(1, 1, 1, 1, 1, 193),
+   list(1, 1, 1, 1, 0, 4),
+   list(1, 1, 1, 2, 1, 191),
+   list(1, 1, 2, 0, 8),
+   list(1, 1, 3, 1, 200))

Next, let’s define node labels:

R> nodelabels <- list(
+   included=c("Randomized"="1","Excluded"="0"),
+   randgrp=c(
+     "Randomized to receive 10 d of remdesivir"="1",
+     "Randomized to receive 5 d of remdesivir"="2",
+     "Randomized to continue standard care"="3"),
+   started=c(
+     "Did not start remdesivir"="0",
+     "Started remdesivir"="1"))

Having set up these objects, the code to produce a CONSORT-style diagram is fairly straightforward. In particular, the follow parameter makes it easy to specify which branches of the tree should be retained.
patients screened
612
Excluded
16
(Withdrew consent 3)
(Ineligible 13)
Randomized
596
Randomized to receive
10 d of remdesivir
197
Randomized to receive
5 d of remdesivir
199
Randomized to continue
standard care
200
Did not start remdesivir
4
Started remdesivir
193
Did not start remdesivir
8
Started remdesivir
191

Figure 24: A variable tree providing a CONSORT-style diagram for the Remdesivir trial.

5. Case Study: Ottawa Police Service Traffic Stops Data

Following a 2005 racial profiling complaint to the Ontario Human Rights Commission, the Ottawa Police Service agreed to collect race data in traffic stops, known as the Traffic Stop Race Data Collection Project (TSRDCP). The TSRDCP required police officers to record their perception of the driver’s race, for traffic stops over a two-year period from June 27, 2013 to June 26, 2015. A data set representing these traffic stops was made public (https://www.ottawapolice.ca/en/news-and-community/race-archive.aspx).

Important questions concern whether some racialized or ethnic groups are stopped at a rate disproportionate to overall makeup of the population. This requires external data, not presented here. See the report by researchers at York University, dated October 2016, for a comprehensive analysis: https://www.ottawapolice.ca/en/about-us/resources/.TSRDCP_York_Research_Report.pdf

In the York University report, some records from the raw data were removed due to errors. Additionally, since some drivers were stopped more than once, only a single report per driver was included. It was not possible to replicate this last step because driver identifiers were not included in the publicly available data set.
One important variable is the outcome (\texttt{how\_cleared}) of the traffic stop: \textit{charged, warning,} or \textit{final (no action)}. This last outcome is of particular interest, because it means that the driver was neither charged nor given a warning, which may raise the question of whether the stop was actually necessary. Figure 26 shows the percentage of stops with this outcome in each node of a tree for \texttt{race=white $\rightarrow$ age $\rightarrow$ gender} (here race has been dichotomized as white or non-white).

A number of interesting patterns emerge. The following drivers were more likely to receive neither a charge nor a warning: (1) male drivers, within all combinations of race and age; (2) younger drivers, within all combinations of race; and (3) non-white drivers.
Figure 26: Variable tree for race=white → age → gender. Each node also shows the percentage of traffic stops with “final/no action” outcome.

6. Concluding remarks

Variable trees are an intuitive way to represent discrete multivariate data. The \texttt{vtree} package in R provides an implementation of variable trees along with a number of convenient extensions. There are a variety of other methods for displaying discrete multivariate data, and depending on the context, one of these methods be preferable. However, the simple structure of variable trees provides not only ease of interpretation but also considerable generality. We have found that variable trees facilitate iterative data exploration when a statistician is working together with a domain expert.

A key characteristic of variable trees is that the order of variables is important. Sometimes the ordering of variables is natural (e.g. school board → school → teacher), in other cases it is dictated by the research question, and in still other cases the choice of ordering is up to the analyst. Depending on the situation, this may be a strength or a weakness.

While \texttt{vtree} can be used to explore data, it can also be used to generate study-flow diagrams. In recent years there has been growing concern about the “reproducibility crisis” in science (Baker 2016). The design of \texttt{vtree} was influenced by the tidyverse philosophy (Wickham et al. 2019), with its emphasis on reproducible workflows. In order to produce study-flow diagrams using \texttt{vtree}, all of the variables and the corresponding set of inclusion/exclusion steps must
be in a single data frame, which encourages a reproducible workflow. A key barrier to the wider adoption of these diagrams has been the difficulty required to produce them. \texttt{vtree} facilitates reproducible research by making it easy to produce accurate study-flow diagrams.

To conclude, variable trees are an intuitive new data exploration tool for visualizing nested subsets. Applications of variable trees include revealing patterns in data, understanding missingness and producing study-flow diagrams for reproducible research.

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