corVis: An R Package for Visualising Associations and Conditional Associations

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Abstract Correlation matrix displays are important tools to explore multivariate datasets. These displays with other measures of association can summarize interesting patterns to an analyst and assist them in framing questions while performing exploratory data analysis. In this paper, we present new visualisation techniques to visualise association between all the variable pairs in a dataset in a single plot, which is something existing displays lack. Also, we propse new methods to visualise relationship among variable pairs using conditioning. We use different layouts like matrix or linear for our displays. We use seriation in our displays which helps in highlighting interesting patterns easily. The R package `corVis` provides an implementation.

Section 1: Introduction

Correlation matrix display is a popular tool to visually explore correlations among variables while performing Exploratory Data Analysis (EDA) on a multivariate dataset. Popularized by Friendly (2002) as corrgram, these displays are produced by first calculating the correlation among the variables and then plotting these calculated values in a matrix display. With effective ordering techniques, these displays quickly highlight variables which are highly correlated and an analyst interested in building a predictive model could use these displays to remove correlated variables and avoid multicollinearity.

The correlation displays are generally used with one of the Pearson's, Spearman's or Kendall's correlation coefficient and are therefore limited to quantitative variables. An analyst can use one-hot encoding of the qualitative variables in order to use these displays but will need to deal with the high dimensions as a result of the encoding. In addition to the dimensionality problem, it is not easy to assess the overall correlation when using the one-hot encoding. The existing methods to quickly explore association among qualitative variables in a dataset include using proportions or counts with different graphical displays like boxplots or barplots. Using association measures for qualitative pairs similar to correlation for quantitative pairs will help in summarizing the relationship, which then can be displayed like the correlation displays.

Tukey and Tukey introduced scagnostics which are measures for scatterplots (Tukey and Tukey, 1985). Along with scagnostics, they proposed a scagnostics scatterplot matrix which is a visual display to explore and compare these measures for all the variable pairs in a dataset. By comparing multiple measures at once, the unusual variable pairs could be identified and looked at in more detail. In a similar manner, a display comparing association measures will help in finding interesting variable pairs. Many association measures have been proposed to summarize different types of relationships. The most commonly used measure is Pearson's correlation coefficient which captures any linear trend present between the variables. Other popular measures include Kendall's or Spearman's rank correlation coefficient which are non-parametric measures and looks for monotonic relationship. Distance correlation (Székely et al., 2007) is an important measure useful in exploring non-linear relationships. The information theory measure maximal information coefficient (MIC) (Reshef et al., 2011) is capable of summarizing complex relationships. With effective displaying techniques, the multiple measures of association provide a comparison tool that assist an analyst to reveal structure present in the data.

Small multiples (or Trellis display) is a simple yet powerful approach to compare partitions of data and understand multidimensional datasets (Tufte, 1986). The display is produced by splitting the data into groups by a conditioning variable and then plotting the data for each group. Such displays allow analysts to quickly infer about the impact of the conditioning variable. A similar idea applied to displays of association measures (correlation plot) will help uncover underlying patterns in the data. One such pattern is Simpson's paradox which can be detected by comparing Pearson's correlation for data at overall level versus individual levels of the conditioning variable.

In this paper, we propose extensions of the correlation plot and new visualizations which look at variables of mixed type, multiple association measures and conditional associations. These displays are implemented in the R package **corVis**. The next section provides a review of existing packages which deal with correlation displays and a quick background on association measures and the packages used for calculating them. Then we describe our approach to calculate the association measures, followed by visualizations of associations and conditional associations. We conclude with a summary and future work.

Section 2: Background

In this section we provide a brief review of existing packages used for correlation displays and association measure calculation.

Section 2.1: Literature Review on Correlation Displays

According to Hills (1969), the first and sometimes only impression gained by looking at a large correlation matrix is its largeness. In order to explore a large correlation matrix Hills (1969) proposed a QQ plot of the entries of the correlation matrix. According to Murdoch and Chow (1996), they proposed a more effective display for exploring a large correlation matrix. Murdoch and Chow (1996) replaced the entries in a correlation matrix by an ellipse where the parameters of ellipse were scaled to the correlation value. These displays are called as correlation matrix displays.

The correlation matrix display is an important tool to explore association among variables in a multivariate analysis. The display was made popular by Friendly (2002) who called them corrgrams, wherein he rendered the correlation values of p numeric variables in a $p \times p$ matrix layout with shaded squares, bars, ellipses, or circular 'pac-man' symbols. The main goal of these displays is to render the correlation patterns in a dataset.

Table 1 provides a list of packages available in R which either calculate correlations, visualise correlations or both. The displays provided by each of the packages are listed, as are the correlations or associations calculated, in particular whether association measures are provided for factor variables or mixed numeric-factor pairs. We also summarise whether packages provide conditional displays of association, by which we mean displays for each of the levels of a categorical variable.

The R package **corrplot** (Wei and Simko, 2021) provides an implementation of the Friendly (2002) paper. It serves as a visual exploratory tool for correlation matrices and includes various variable ordering methods which place highly-correlated pairs of variables nearby, making it easier to quickly identify groups of variables with high mutual correlation.

The package **corrr** (Kuhn et al., 2020) organises correlations as tidy data, so leveraging the data manipulation and visualisation tools of the **tidyverse** (Wickham et al., 2019). In addition to various matrix displays, the package offers network displays where line-thickness encodes correlation magnitude, with a filtering option to discard low-correlation edges.

CORRGRAPHER

The package **linkspotter** (Samba, 2020) offers a variety of association measures (list some) in addition to correlation, where the measure used depends on whether the variables are both numerical, categorical or mixed. The results are visualised in a network plot, which may be packaged into an interactive shiny application.

We include our own package corvis in the table, which has new features not available elsewhere, in particular simulaneous display of multiple association measures, and association displays stratified by levels of a grouping variable. This will be described further in the following section.

ALL THIS STUFF ABOUT CORVIS SHOULD APPEAR IN THE SECTION ABOUT CORVIS.

There have been other extensions to correlation displays which are useful when dealing with high dimensional datasets. Buja et al. (2016) proposed Association Navigator which is an interactive visualization tool for large correlation matrices with upto 2000 variables. The R package **scorrplot** (Gerber, 2022) produces an interactive scatterplot for exploring pairwise correlations in a large dataset by projecting variables as points with respect to some user-selected variables on a scatterplot, driven by geometric interpretation of correlation. A user can update variables of interest and can create tours of the correlation space between different projections of the data using this tool. I DO NOT UNDERSTAND ANY OF THIS ABOUT SCORRPLOT. TRY AGAIN.

REMOVE CORHEAT FROM TABLE

The R package **correlationfunnel** offers a novel display which assists in feature selection in a setting with a single response and many predictor variables. All numeric variables including the response are binned. All (now categorical) variables in the resulting dataset are one-hot encoded and Pearson's correlation calculated with the response categories. The correlations are visualised in a dot-plot display, where predictors are ordered by maximum correlation magnitude. Correlations between one-hot encoded variables are challenging to interpret, especially as the number of levels increase. In corVis we offer a similar dot-plot display, but showing multiple correlation or association measures, or alternatively measures stratified by a grouping variable.

Table 1: List of the R packages dealing with correlation or correlation displays with information on whether the plots display multiple measures, conditional display of measures and mixed variables in a single plot

Package	Display	MultipleMeasures	ConditionalPlot	MixedVariables
coreheat	heatmap			
corrplot	heatmap			
corrr	heatmap/network			
corrgrapher	network			
corrarray	no display		Yes	
linkspotter	network			Yes
correlation	heatmap/network			
corVis	heatmap/matrix/linear	Yes	Yes	Yes

Section 2.2: Literature Review on Association Measures

An association measure can be defined as a numerical summary quantifying the relationship between two or more variables. For example, Pearson's correlation coefficient summarizes the strength and direction of the linear relationship present between two numeric variables and is in the range $[-1, 1]$. Kendall's or Spearman's rank correlation coefficient are other popular measures which assess montonic relationship among two numeric variables and are in the range $[-1, 1]$. As these measures are limited to linear or monotonic relationships, there's a need to use association measures which can capture complex relationships (like periodic). The distance correlation coefficient (Székely et al., 2007) is one such measure which looks for the non-linear association between two numeric variables and summarizes it in $[0, 1]$. Similarly, MIC (Reshef et al., 2011) is capable of summarizing non-linear as well as periodic relationships between numeric variables. In addition to association measures for numeric variables, association measures for ordinal or nominal or mixed variables will help an analyst in exploring a multivariate dataset. Taha and Hadi (2016) provides an overview of the association measures used for categorical or mixed data.

We use multiple association measures in a single display for different variable pairs which serves as a comparison tool while exploring association in a dataset and assist in identifying unusual variable pairs. These multiple measures can be displayed in a scatterplot matrix similar to what Tukey and Tukey (1985) proposed. They suggested that scatterplot matrix of the scagnostics measures, which are measures summarizing a scatterplot, can be used to identify unusual scatterplots or variable pairs. Wilkinson et al. (2005) used this idea with their graph-theoretic scagnostic measures to highlight unusual scatterplots. Similarly, Kuhn et al. (2013) have used this idea in a predictive modeling context. They have produced a scatterplot matrix of the measures between the response and continuous predictors such as Pearson's correlation coefficient, pseudo-R^2 from the locally weighted regression model, MIC and Spearman's rank correlation coefficient to explore the predictor importance during feature selection step. These displays show the importance of comparing multiple association measures at once for different variable pairs. In this paper, we propose different visualization techniques to compare multiple association measures for all the variable pairs in a dataset which can assist a user in finding interesting patterns.

Section 3: Introducing corVis

corVis is an R package which calculates measures of association for every variable pair in a dataset and helps in visualising these associations in different ways. The package can also calculate and visualise the pairwise association measures conditionally at different levels of a grouping variable. The package also focuses on the new visualisation techniques such as display with multiple measures for the calculated association and conditional association measures for every variable pair in the dataset. Efficient seriation techniques have been included to order and highlight interesting relationships. These ordered association and conditional association displays can help find interesting patterns in the dataset.

Most of the existing correlation displays are limited to numeric pairs of variables. This package extends these displays to every variable pair. In addition to it, we introduce novel visualization methods for correlation or association analysis during EDA. These new displays help an analyst to quickly discover any unusual variable pair(s) and understand the conditional pattern present in the dataset.

Table 2: List of the functions available in the package for calculating different association measures along with the packages used for calculation.

funName	typeX	typeY	from	symmetric	range
tbl_cor	numerical	numerical	stats::cor	TRUE	[-1,1]
tbl_dcor	numerical	numerical	energy::dcor2d	TRUE	[0,1]
tbl_mine	numerical	numerical	minerva::mine	TRUE	[0,1]
tbl_polycor	ordinal	ordinal	polycor::polychor	TRUE	[-1,1]
tbl_tau	ordinal	ordinal	DescTools::KendalTauA,B,C,W	TRUE	[-1,1]
tbl_gkTau	nominal	nominal	DescTools::GoodmanKruskalTau	FALSE	[0,1]
tbl_gkLambda	nominal	nominal	DescTools::GoodmanKruskalTau	TRUE	[0,1]
tbl_gkGamma	nominal	nominal	DescTools::GoodmanKruskalTau	TRUE	[0,1]
tbl_uncertainty	nominal	nominal	DescTools::UncertCoef	TRUE	[0,1]
tbl_chi	nominal	nominal	DescTools::ContCoef	TRUE	[0,1]
tbl_cancor	nominal	nominal	corVis	TRUE	[0,1]
tbl_cancor	nominal	numerical	corVis	TRUE	[0,1]
tbl_nmi	any	any	corVis	TRUE	[0,1]
tbl_easy	any	any	correlation::correlation	TRUE	[-1,1]

Section 4: corVis: Calculating Association

This section describes the calculation of association measures in our package **corVis**. The package provides a collection of various measures of association which quantifies the relationship between two variables. The association measures available in the package are not limited to numeric variables and are used with nominal, ordinal and mixed variable pairs as well. Table 2 lists different functions provided in the package to calculate measures of association. The `funName` represents the function name used to calculate measure(s) of associations in this package. The `typeX` and `typeY` columns provide the information on types of variables which can be used with the corresponding functions. The `X` or `Y` variable can be anyone out of numeric, nominal, ordinal or any. The `from` column corresponds to the package functions used to calculate the association measures by the function under `funName`. The `symmetric` column represents if the measure is symmetric i.e. if the value of measure is same regardless of the order of variables. The last column provides the range of values for these measures. The function `tbl_easy` can be used to calculate association measures available in the R package `correlation` which can use different variable types. The highlighted functions in 2 calculate the association measures which have been implemented in this package.

For numeric pairs of variables, this package provides a range of association measures. The popular correlation coefficients like Pearson's or Spearman's or Kendall's are calculated using `tbl_cor` function. The measures such as distance correlation or MIC which assess more complex relationship are calculated using `tbl_dcor` or `tbl_mine` respectively. The association measures available in the package for the ordinal pairs of variables are polychoric correlation and Kendall's coefficients which are calculated using `tbl_polycor` or `tbl_tau` respectively. For nominal pairs of variables, the functions like `tbl_gkTau`, `tbl_gkLambda`, `tbl_gkGamma`, `tbl_uncertainty`, `tbl_chi`, `tbl_cancor` are used for exploring association among the variables. These measures are consistent with respect to the order of the nominal variable which some of the existing measures lack.

The association measures available for mixed variable pairs are limited in the literature.The function `tbl_cancor` implemented in the package calculates canonical correlation for mixed pairs of variables and is useful in exploring association among mixed variables. The goal of the canonical correlation analysis is to maximize the association between the low-dimensional projections of two sets of variables (Härdle and Simar, 2019). We calculate canonical correlation between a numeric variable and a nominal variable by first converting the nominal variable into dummy variables and then calculating the correlation between the continuous variable and set of dummy variables.

Calculating association for a single type of variable pairs

We introduce a method which creates a tibble structure for the variable pairs in a dataset along with calculated association measure. The package contains various functions (shown in Table 2) for different association measures in the form `tbl_*` to calculate them. For example, a user might be interested in calculating distance correlation for numeric pair of variables in a dataset. This can be done by using `tbl_dcor`.

```
df <- penguins
distance <- tbl_dcor(df)
head(distance)

#> # A tibble: 6 x 4
#>   x                 y              measure measure_type
#>   <chr>             <chr>            <dbl> <chr>
#> 1 bill_depth_mm     bill_length_mm  0.387  dcor
#> 2 flipper_length_mm bill_length_mm  0.666  dcor
#> 3 body_mass_g       bill_length_mm  0.587  dcor
#> 4 year              bill_length_mm  0.0784 dcor
#> 5 flipper_length_mm bill_depth_mm   0.704  dcor
#> 6 body_mass_g       bill_depth_mm   0.614  dcor
```

Similarly, one can use `tbl_nmi` to calculate normalised mutual information for numeric, nominal and mixed pair of variables.

```
nmi <- tbl_nmi(df)
head(nmi)

#> # A tibble: 6 x 4
#>   x                 y         measure measure_type
#>   <chr>             <chr>       <dbl> <chr>
#> 1 island            species 0.507     nmi
#> 2 bill_length_mm    species 0.353     nmi
#> 3 bill_depth_mm     species 0.315     nmi
#> 4 flipper_length_mm species 0.343     nmi
#> 5 body_mass_g       species 0.300     nmi
#> 6 sex               species 0.0000854 nmi
```

The tibble output for the functions mentioned in Table 2 has the following structure:

- `x` and `y` representing a pair of variables
- `measure` representing the calculated value for association measure
- `measure_type` representing the association measure calculated for `x` and `y` pair.

The variable pairs in the output are unique pairs and a subset of all the variable pairs of a dataset where $x \neq y$. As explained earlier, the `measure_type` represents the association measure calculated for a specific type of variable pair

Calculating association measures for whole dataset

`calc_assoc` can be used to calculate association measures for all the variable pairs in the dataset at once in a tibble structure. In addition to tibble structure, the output also has `pairwise` and `data.frame` class which are important class attributes for producing visual summaries in this package.

The function `calc_assoc` has a `types` argument which is basically a tibble of the association measure to be calculated for different variable pairs. The default tibble of measures is `default_assoc()` which calculates Pearson's correlation if both the variables are numeric, Kendall's tau-b if both the variables are ordinal, canonical correlation if one is factor and other is numeric and canonical correlation for the rest of the variable pairs.

```
default_measures <- default_assoc()
default_measures

#> # A tibble: 4 x 4
#>   funName    typeX   typeY   argList
#>   <chr>      <chr>   <chr>   <list>
#> 1 tbl_cor    numeric numeric <NULL>
#> 2 tbl_tau    ordered ordered <NULL>
#> 3 tbl_cancor factor  numeric <NULL>
#> 4 tbl_cancor other   other   <NULL>

penguin_assoc <- calc_assoc(df,types = default_assoc())
glimpse(penguin_assoc)
```

```
#> Rows: 28
#> Columns: 4
#> $ x            <chr> "island", "bill_length_mm", "bill_depth_mm", "flipper_len~
#> $ y            <chr> "species", "species", "species", "species", "species", "s~
#> $ measure      <dbl> 0.81328762, 0.84131393, 0.82447508, 0.88217284, 0.8183348~
#> $ measure_type <chr> "cancor", "cancor", "cancor", "cancor", "cancor", "cancor~
```

```
class(penguin_assoc)
```

```
#> [1] "pairwise"   "tbl_df"     "tbl"        "data.frame"
```

An analyst can update these measures using the `update_assoc` function where one can specify a `tbl_*` function to calculate association measure depending on the variable pair in the dataset and a method if it calculates more than one measure.

```
updated_assoc <- update_assoc(default=default_assoc(),
                              num_pair = "tbl_cor",
                              num_pair_argList = "spearman",
                              mixed_pair = "tbl_cancor",
                              other_pair = "tbl_nmi")
updated_assoc
```

```
#> # A tibble: 4 x 4
#>   funName    typeX   typeY   argList
#>   <chr>      <chr>   <chr>   <list>
#> 1 tbl_cor    numeric numeric <chr [1]>
#> 2 tbl_tau    ordered ordered <NULL>
#> 3 tbl_cancor factor  numeric <NULL>
#> 4 tbl_nmi    other   other   <NULL>
```

If a user is interested in calculating multiple association measures for a type of variable pair, it can be done by using the `calc_assoc` and `update_assoc` together for calculating different association measures and then merging the output tibbles.

```
updated_penguin_assoc <- calc_assoc(df, types = updated_assoc)
head(updated_penguin_assoc)
```

```
#> # A tibble: 6 x 4
#>   x                 y         measure measure_type
#>   <chr>             <chr>       <dbl> <chr>
#> 1 island            species 0.507     nmi
#> 2 bill_length_mm    species 0.841     cancor
#> 3 bill_depth_mm     species 0.824     cancor
#> 4 flipper_length_mm species 0.882     cancor
#> 5 body_mass_g       species 0.818     cancor
#> 6 sex               species 0.0000854 nmi
```

Calculating conditional association

`calc_assoc_by` is used to calculate association measures for all the variable pairs at different levels of a categorical variable. This helps in exploring the conditional associations and find out the differences between the groups of the conditioning variable. The output of this function is a tibble structure with `pairwise` and `data.frame` as additional class attributes. The `calc_assoc_by` function has a `by` argument which is used for the grouping variable and it needs to be categorical.

```
penguin_assoc_by <- calc_assoc_by(df,by = "sex")
```

The `calc_assoc_by` function also has a `types` argument which can be updated similarly to `calc_assoc`.

```
updated_assoc <- update_assoc(num_pair = "tbl_cor",
                              num_pair_argList = "spearman",
                              mixed_pair = "tbl_cancor",
                              other_pair = "tbl_nmi")
updated_penguin_assoc_by <- calc_assoc_by(df,by = "sex", types = updated_assoc)
head(updated_penguin_assoc_by)
```

```
#> # A tibble: 6 x 5
#>   x                 y       measure measure_type by
#>   <chr>             <chr>     <dbl> <chr>        <fct>
#> 1 island            species  0.502  nmi          female
#> 2 bill_length_mm    species  0.885  cancor       female
#> 3 bill_depth_mm     species  0.900  cancor       female
#> 4 flipper_length_mm species  0.914  cancor       female
#> 5 body_mass_g       species  0.911  cancor       female
#> 6 year              species  0.0457 cancor       female
```

By default, the function calculates the association measures for all the variable pairs at different levels of the grouping variable and the pairwise association measures for the ungrouped data (`overall`). This behavior can be changed by setting `include.overall` to `FALSE`.

```
penguin_assoc_by <- calc_assoc_by(df,by = "sex",include.overall = FALSE)
```

The tibble output for `calc_assoc_by` has the similar structure as `calc_assoc` with an additional `by` column representing the levels of the categorical variable used in the function. The `x` and `y` variables in the output are repeated for every level of `by` variable. In order to have multiple `by` variables, the function `calc_assoc_by` is used multiple times with a different `by` variable each time and then the multiple outputs are binded row wise. For calculating multiple measures for a specific variable type, one can use `update_assoc` with `calc_assoc_by` and then can merge these multiple tibble outputs.

Section 5: corVis: Visualising Association

We propose novel visualisations to display association for every variable pair in a dataset in a single plot and show multiple bivariate measures of association simultaneously to find out interesting patterns. Efficient seriation techniques have been included to order and highlight interesting relationships. These ordered association and conditional association displays can help find interesting patterns in the dataset. While designing these displays we considered matrix-type, linear and network-based layouts. A matrix-type layout simplifies lookup, and different measures may be displayed on the upper and lower diagonal. Linear layouts are more space-efficient than matrix plots, but lookup is more challenging. Variable pairs can be ordered by relevance (usually difference in measures of association or across the factor levels), and less relevant pairs can be omitted.

Figure 1 shows this display for every variable pair in the `penguins` dataset from the `palmerpenguins` package. It shows a high positive Pearson's correlation among `flipper_length` and `body_mass`, `flipper_length` and `bill_length`, and `bill_length` and `bodymass`. There seems to be a strong negative Pearson's correlation between `flipper_length` and `bill_depth`, and `bill_depth` and `body_mass`. The plot also shows that there is a high canonical correlation between `species` and other variables except `year` and `sex`, and a high canonical correlation between `island` and `species`, which traditional correlation matrix display would omit as they are limited to numeric variable pairs only. The variables in the display are ordered using average linkage clustering method to find out highly associated variables quickly.

We can also calculate multiple association measures for all the variable pairs in the dataset and compare them. This will help in finding out pairs of variables with a high difference among different measures and one can investigate these bivariate relationships in more detail. The `pairwise_summary_plot` function can be used to compare various measures using the matrix layout. It plots multiple measures among the variable pairs as bars, where each bar represents one measure of association. Figure 2 shows a matrix layout comparing Pearson's and Spearman's correlation coefficient for the numeric variable pairs in `penguins` data.

In addition to matrix layout, we can also use linear layouts for comparing multiple measures. Figure 3 shows a linear layout comparing multiple association measures for all the variable pairs in the penguins data. Linear layouts seems to be more suitable when comparing high number of association measures.

Visualising Conditional Association

The package includes a function `calc_assoc_by` which calculates the pairwise association at different levels of a categorical conditioning variable. This helps in finding out interesting variable triples which can be explored further prior to modeling. Figure 4 shows a conditional association plot for the `penguins` data. Each cell corresponding to a variable pair shows three bars which correspond to the association measure (Pearson's correlation for numeric pair and Normalized mutual information

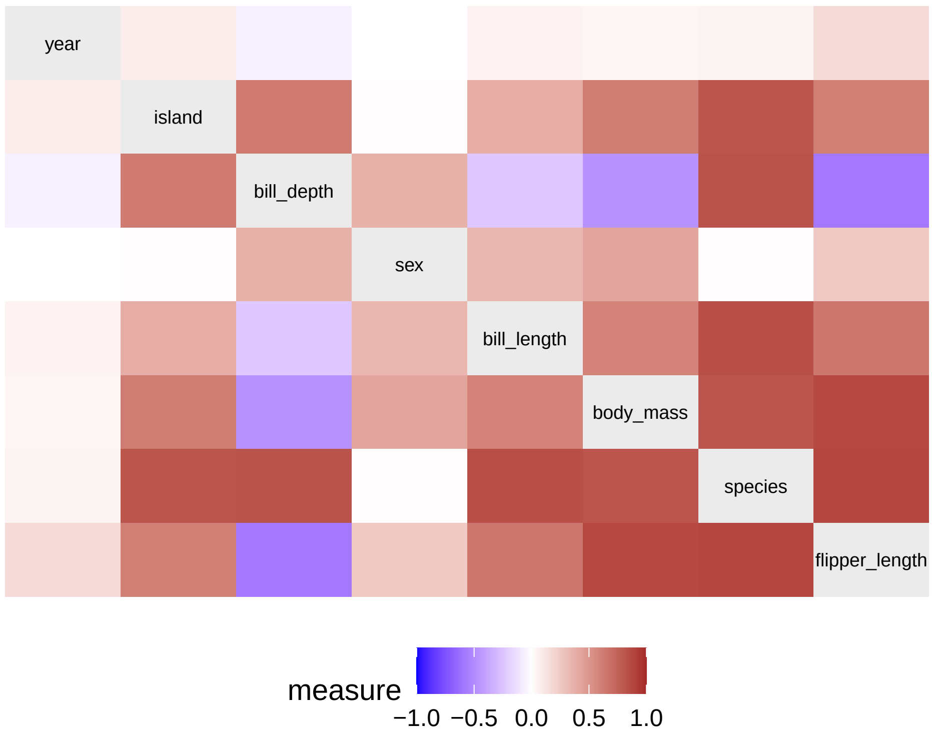

Figure 1: Association matrix display for penguins data showing Pearson's correlation for numeric variable pairs, canonical correlation for mixed variable pairs and categorical variable pairs.

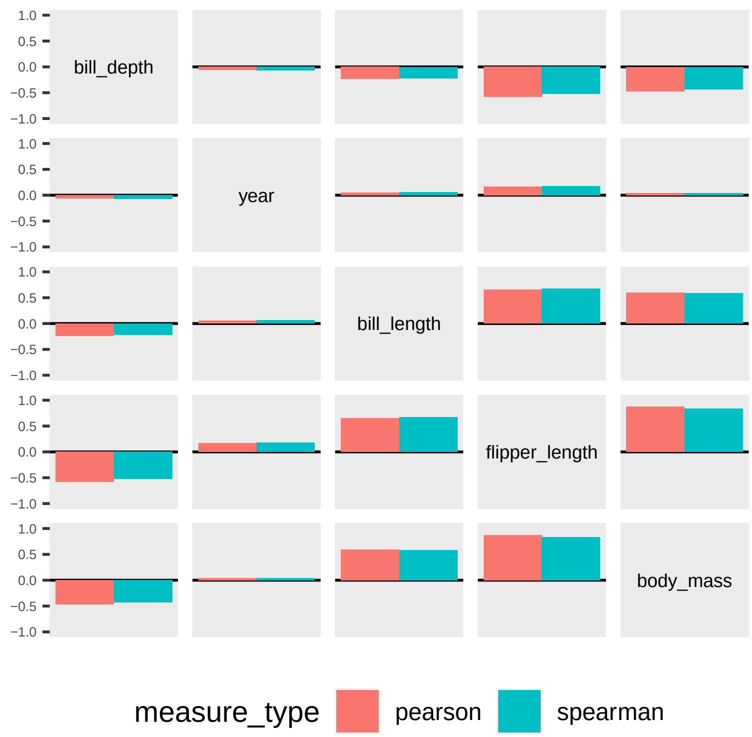

Figure 2: Matrix display comparing Pearson's and Spearman's correlation coefficient. All the variable pairs have similar values for both correlations.

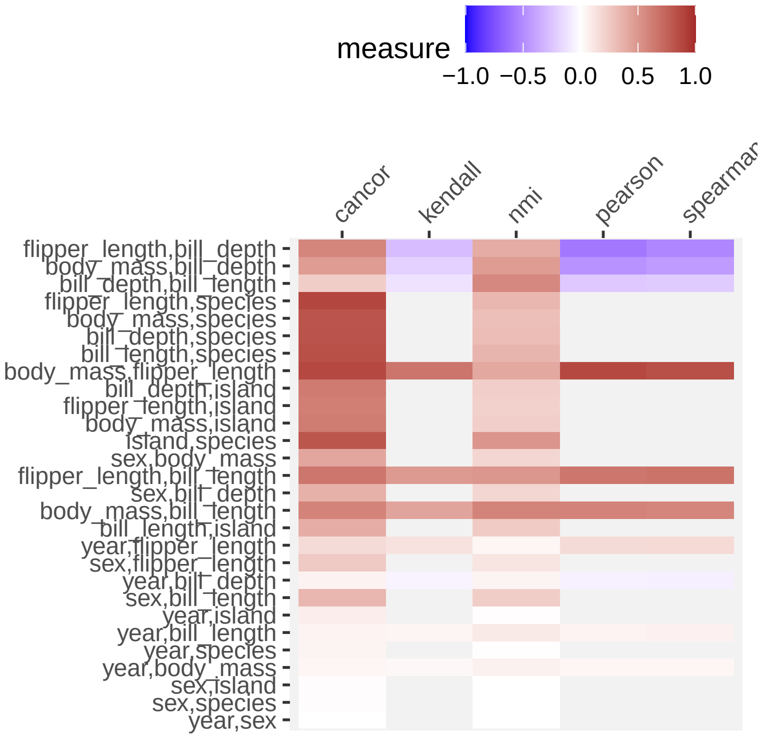

Figure 3: Comparing multiple association measures using a linear layout. The display has variable pairs on the Y-axis and association measures on the X-axis. The cell corresponding to a variable pair and an association measure has been colored grey showing that the measure is not defined for corresponding pair.

for other combination of variables) calculated at the levels of conditioning variable `island`. The dashed line represents the overall association measure. The plot shows that there is a high value for normalised mutual information between bill_length_mm and species for the penguins which lived in `Biscoe` island compared to the penguins which lived in `Dream` island. It can also be seen that the cell corresponding to variable pair flipper_length_mm and bill_depth_mm has a high negative overall Pearson's correlation and for the penguins which lived in `Biscoe` island but positive correlation for penguins which lived in `Dream` and `Torgersen` island. This is an instance of Simpson's paradox which can be taken into account during the modeling step.

We also provide a functionality for highlighting interesting patterns like Simpson's paradox. Figure 5 shows the matrix plot with highlighted cells for the variable pairs where Simpson's paradox is present.

The cells can also be highlighted on the basis of a score calculated by the user. This can be done by providing a dataframe with pairs of variables to highlight and a score for highlighting variable pairs. The cells with high score will have a thicker border compared to cells with low score. Figure 6 shows highlighted cells on the basis of a score provided for a subset of variable pairs.

We can also use linear layouts for displaying conditional association. Figure 7 shows a funnel-like linear display for conditional association measures with all the variable pairs on the y-axis, the value of association measure on x-axis and color of the points representing the level of the grouping variable. The linear layout becomes more useful over the matrix layout when the number of variables and number of levels of grouping variable are high.

Bibliography

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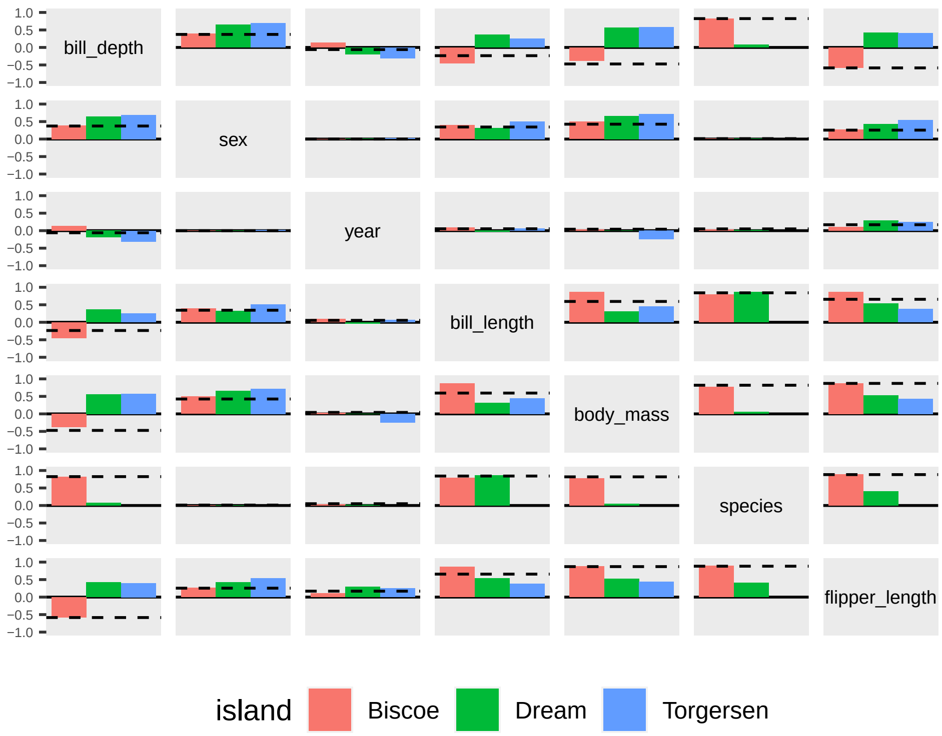

Figure 4: Conditional Association plot for penguins data showing Pearson's correlation for numeric pairs and normalised mutual information for categorical or mixed pairs. The bars in each cell represent the value for asssociation measure colored by the conditioning variable 'island'. The dashed line in each cell represents overall value of the association measure.

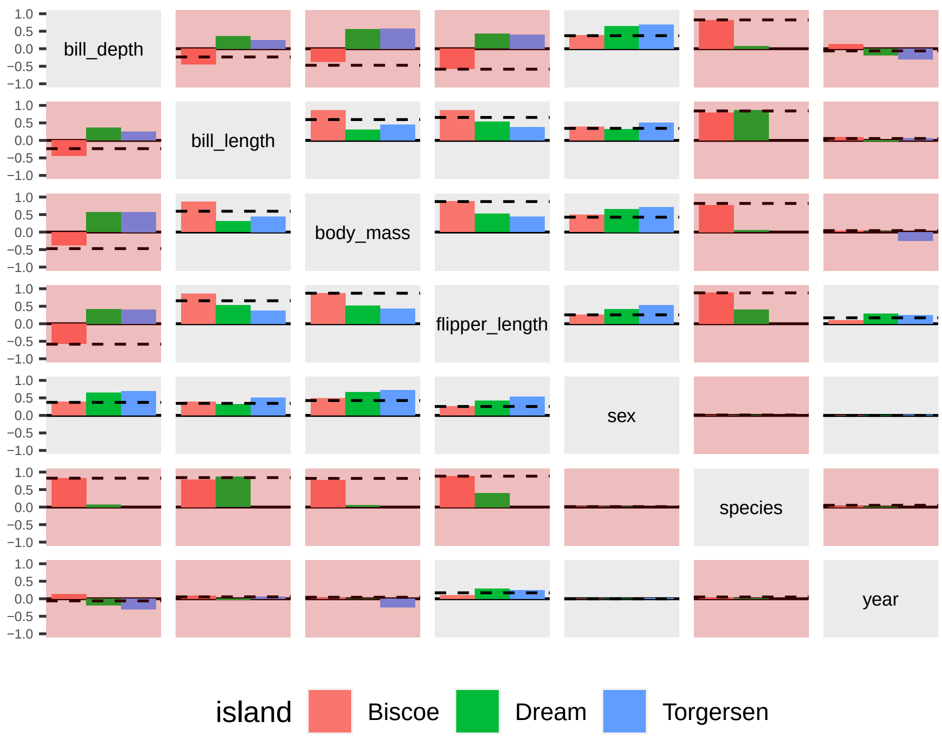

Figure 5: Conditional Association plot with examples of Simpson's paradox

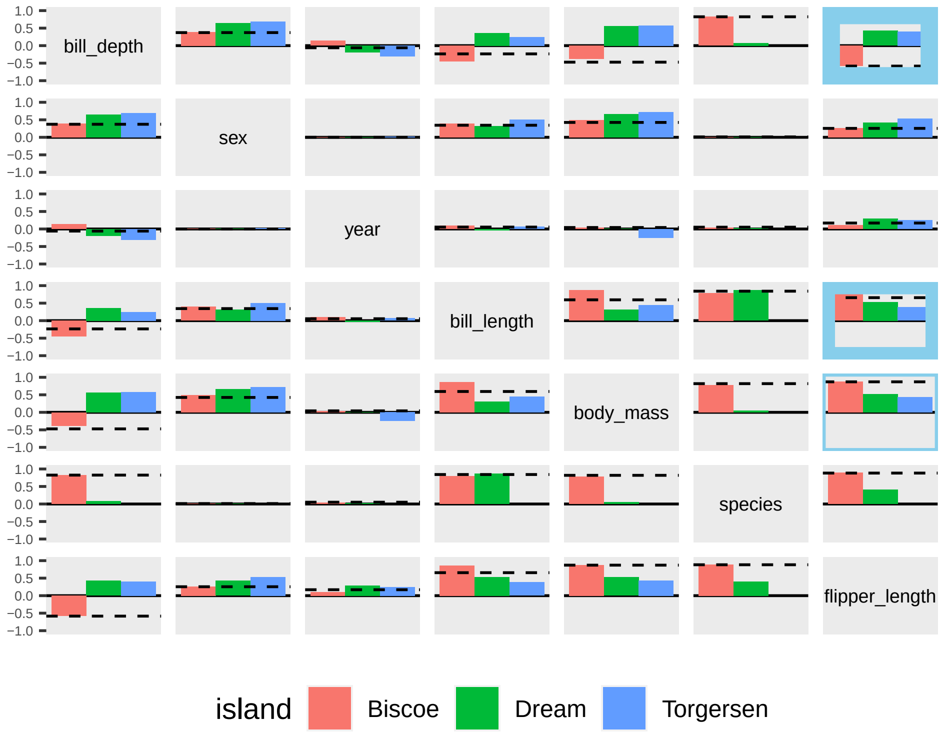

Figure 6: Conditional Association plot with manual highlighting

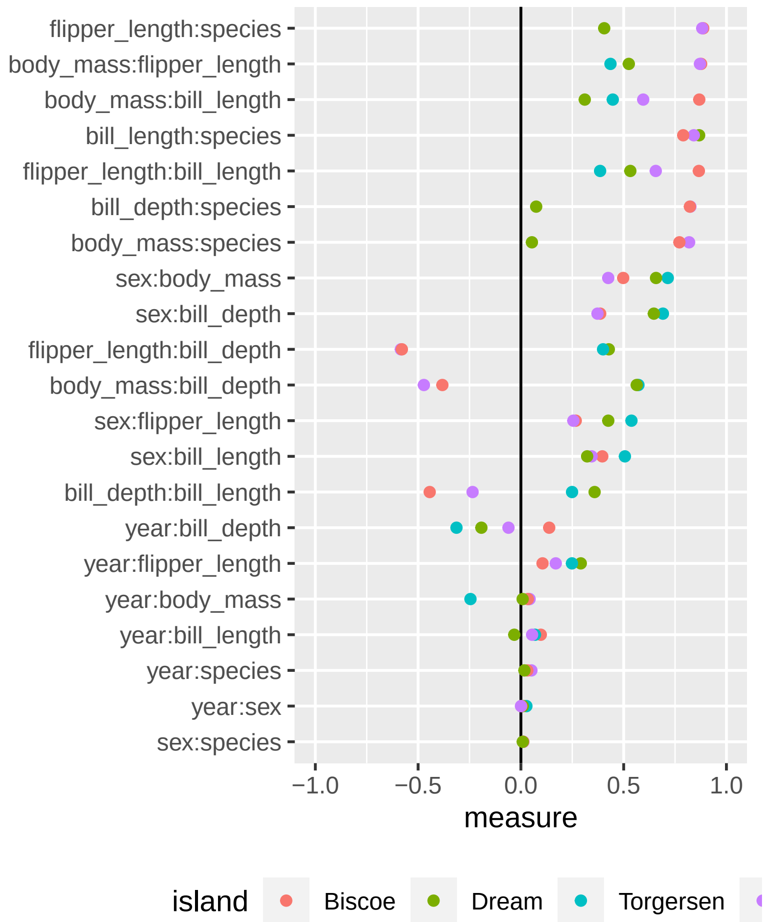

Figure 7: Conditional Association plot using linear layout.The display has variable pairs on the Y-axis and the value of association measures on the X-axis. The points corresponding to every variable pair represents the value of association measure for different levels of the conditioning variable and the overall value of association measure.

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