



Decision Intelligence
for Organizations in
Network Environments

User Manual

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July 2021

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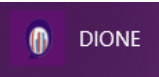

Introduction

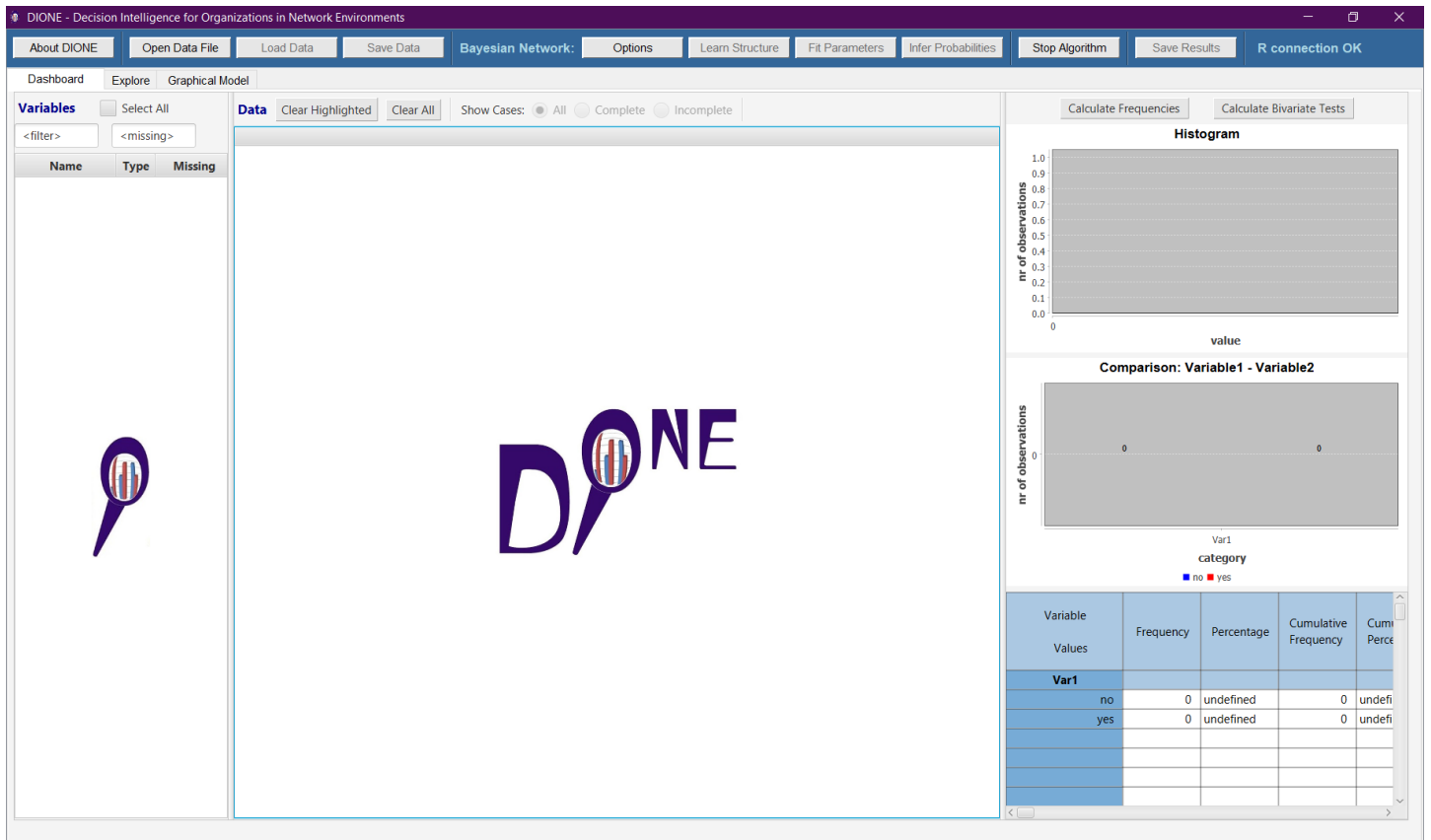
Data analysis with **DIONE** is typically done in four main steps:

1. Load the data to be analysed. In the current version data can be loaded from CSV files and from common statistics data file formats. When loading data from a CSV file, the data file is assumed to have a header record containing variable names and any number of data records containing values of the variables. Variable names and values are separated by commas (,), tabs (\t), semicolons (;), colons(:) or vertical slashes (/) and optionally enclosed in double quotes (“”). Each record is delimited by a line break (CRLF).
2. Explore the data using standard statistical tools to get a better intuition of data characteristics, trends, relationships, etc. Each variable can easily be inspected individually, showing plots of its distribution and statistical information. Pairs of variables can easily be compared for a first intuition of possible relationships between variables.
3. Recode data, if needed: for example, transform numerical data to categorical data or group categories of categorical data to new categories.
4. Analyse the data using sophisticated data analysis algorithms. At present multivariate analysis is implemented by learning a Bayesian network from the data values of the variables of interest, which will be represented by nodes in the network. The learned network can then be used for inference and for estimating effects of interventions.
5. Save data and/or analysis results. After selecting and/or recoding data for your analysis, you may wish to keep these data to continue your analysis at another time. **DIONE** makes it easy to do this. It is also easy to save analysis results as tables, graphs and charts, ready for your publications.

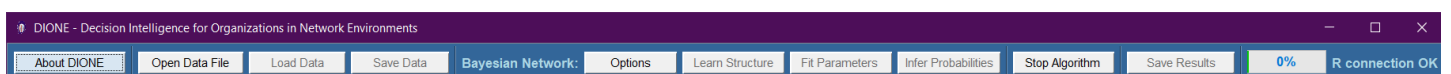
This guide shows and explains these steps with a simple demonstration data set with fictitious data on variables such as having visited a country with a high incidence of tuberculosis, smoking, age, having the diseases of tuberculosis or lung cancer, and X-ray results. You can of course do similar analyses of your own data.

Start DIONE

To launch **DIONE**, double-click the  desktop icon or select  in the Windows Start Menu . The **DIONE** screen now looks like this:



At the top of the screen there is a toolbar with buttons for loading and saving data and for data analysis. To the right of the buttons there is an area displaying messages about what the program is doing (in light blue), including possible error messages (in red):

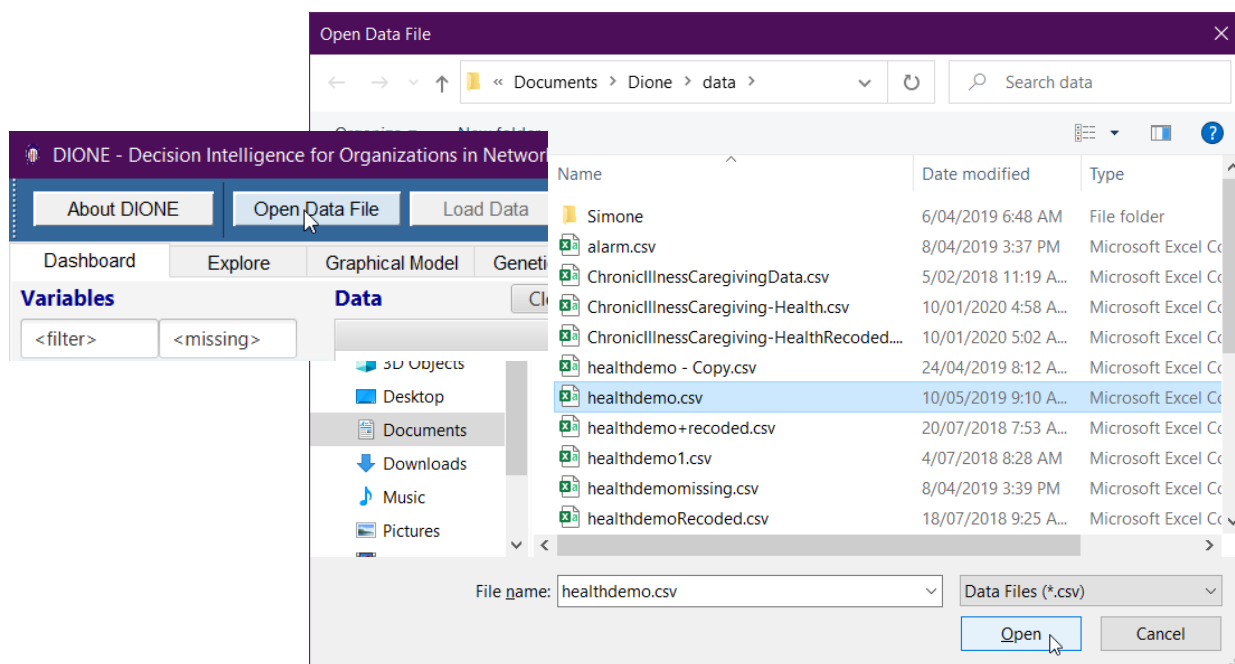


The main area of the screen has three tabs: **Dashboard**, **Explore** and **Graphical Model**. Initially the **Dashboard** tab is selected.

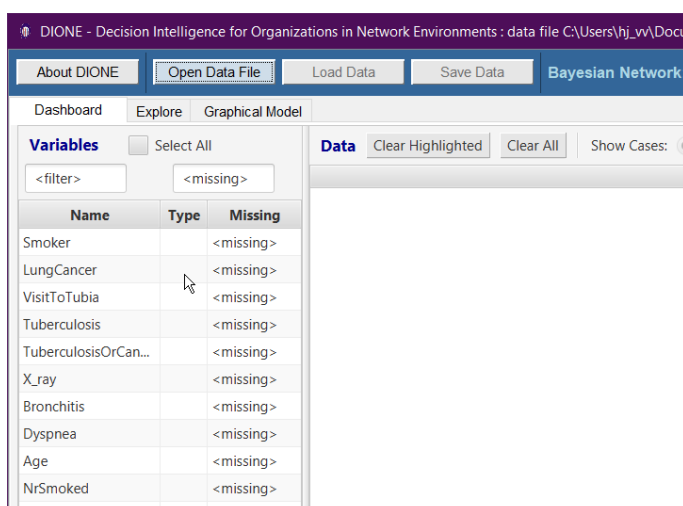
In the **Dashboard** tab there are two tables: after loading data the **Variables** table shows the variable names and the **Data** table shows data of selected variables. At the top right-hand side there are visual representations of selected data, and at the bottom right-hand side there is a table with frequency distributions and test results of selected data. In the **Explore** tab a more detailed view of exploratory data analysis results is shown and there are options to recode data. The **Graphical Model** tab will show results of Bayesian network learning and inference algorithms.

Load Data

Data can be loaded from text (.csv) files and from common statistics data file formats, including data files with extension .sav, .dta or .sas7bdat. Column headers of a text (.csv) data file must be variable names. In this guide the text file healthdemo.csv is used. To open a data file, press the **Open Data File** button to bring up the **Open Data File** dialog. Now select the data file to analyse and press the **Open** button:



Now you see the variable names (column headers in the text file) in the **Variables** table at the left of the screen (data values will be loaded in the next step):



The second column in the **Variables** table is the variables' data type (categorical, ordinal or numerical), to be shown after loading the data values. The third column shows the code for missing values in the data (default is <missing>, but this can be changed if needed).

The column **Type** in the **Variables** table shows the data type of the variables, categorical (C), ordinal (O) or numerical (N). **DIONE** infers the data type from the loaded data. If the data for a variable have text values such as yes or no, the variable is categorical. If the data of a variable consist of numbers, the variable is numerical, unless the number of distinct number values is less than 12, in which case it is assumed the numbers are codes for different levels and the variable is categorical. The data type of a variable can be changed by clicking in the type cell of the variable and selecting a different type, for example making variable **NrSmoked** numerical:

Variable	Type	Missing	yes	yes	no	yes		
TuberculosisOr...	C	<missing>	yes	yes	no	yes	47	6
X_ray	C	<missing>	yes	yes	yes	no	57	4
Bronchitis	C	<missing>	yes	yes	yes	yes	71	10
Dyspnea	C	<missing>	yes	yes	yes	yes	61	6
Age	N	<missing>	yes	yes	no	yes	53	0
NrSmoked	C	<missing>	yes	yes	no	yes	48	4
	O		yes	yes	yes	yes	72	9
	N		yes	yes	yes	yes	46	8
			yes	yes	yes	yes	61	7

If you want to remove variables from the analysis, right-click on the column headers of these variables to highlight them in red. If you change your mind about removing a variable, right-click again on the selected column header. Press button **Clear Highlighted** to remove the variables highlighted in red:

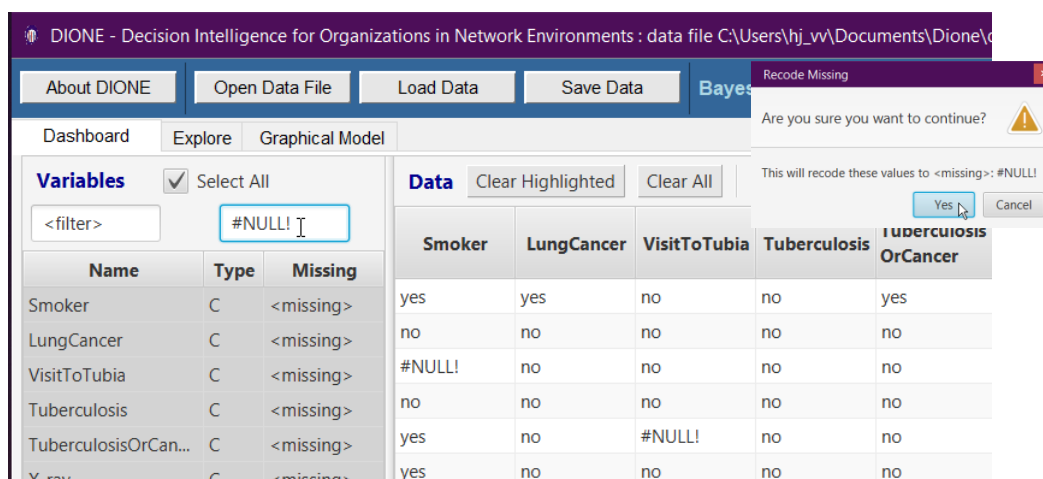
Name	Type	Missing	Smoker	LungCancer	VisitToTubia	Tuberculosis	Tuberculosis Or Cancer	X_ray	Bronchitis	Dyspnea
Smoker	C	<missing>	yes	yes	no	no	yes	yes	yes	yes
LungCancer	C	<missing>	no	yes	no	no	yes	yes	no	no
VisitToTubia	C	<missing>	yes	yes	no	no	yes	yes	no	yes
Tuberculosis	C	<missing>	yes	yes	no	no	yes	yes	yes	yes
TuberculosisOrCan...	C	<missing>	yes	yes	no	no	yes	yes	no	yes
X_ray	C	<missing>	yes	yes	no	no	yes	yes	yes	no
Bronchitis	C	<missing>	yes	yes	no	no	yes	yes	yes	yes
Dyspnea	C	<missing>	yes	yes	no	no	yes	yes	yes	yes
Age	N	<missing>	no	yes	no	no	yes	yes	no	yes
NrSmoked	C	<missing>	yes	yes	no	no	yes	yes	no	yes
			yes	yes	no	no	yes	yes	yes	yes
			yes	yes	no	no	yes	yes	yes	yes

These variables are removed from the **Data** table and will not be used for the Bayesian network analysis but are still loaded. They can be added again to the **Data** table, if desired, by selecting them in the **Variables** table and pressing the Enter key. You can also press button **Clear All** to remove all variables from the **Data** table and start again selecting variables from the **Variables** table.

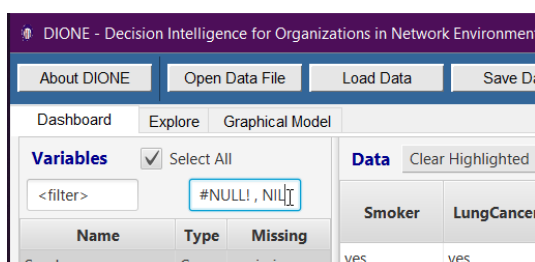
You can also remove variables from the **Variables** table by selecting them and pressing the Delete key to unload them. This way it is easier to remove many variables at a time, but be aware you can no longer access these variables in the current session.

Missing Values

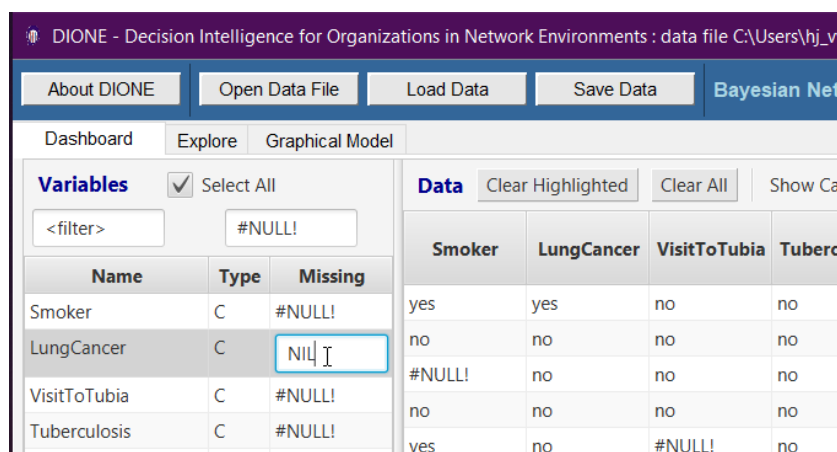
The default code for missing values is `<missing>`. If your data have a special code for missing values, you can set that code in the `<missing>` text box by typing the desired code, pressing the Enter key and confirming the recoding in the next dialog, as in this example with data from file `healthdemomissing1.csv`:



For some data more than one value is considered to represent a missing value. You can set several values as missing value by entering them in the `<missing>` field, separated by commas:



You can also set a code for a specific variable in the **Variables** table row for that variable, for example NIL for variable **LungCancer** instead of #NULL! for all other variables here:



Complete and Incomplete Cases

Each row of loaded data contains a specific combination of values for the variables that are selected for analysis. We call such a combination of values a case. For many analyses, including common Bayesian network structure learning algorithms, it is necessary to have only complete cases. i.e. cases with no missing values for any of the selected variables. In **DIONE** it is easy to inspect complete and incomplete cases for a set of selected variables.

For example, with the data from file `healthdemomissing.csv` and missing value code set to `#NULL!`, check radio button Incomplete :

The screenshot shows the DIONE software interface. The 'Data' table is displayed with the following columns: Smoker, LungCancer, VisitToTubia, Tuberculosis, Tuberculosis OrCancer, X-ray, Bronchitis, and Dyspnea. The 'VisitToTubia' column is highlighted in red, indicating a high percentage of missing values. The 'Show Cases' section shows the 'Incomplete' radio button selected, and the total number of cases is 344.

Variable	Missing
Smoker	#NULL!
LungCancer	#NULL!
VisitToTubia	#NULL!
Tuberculosis	#NULL!
Tuberculosis OrCancer	#NULL!
X-ray	#NULL!
Bronchitis	#NULL!
Dyspnea	#NULL!

The **Data** table now shows the cases with missing values, with missing value codes replaced by the standard code `<missing>` used by **DIONE**. To give more insight in numbers of missing values of all variables, the variables in the **Variables** table are colour-coded in shades of red: darker red means a higher percentage of missing values, so in this example variable **VisitToTubia** has the highest proportion of missing values. Values of a variable can be inspected by double-clicking in the variable's data column in the **Data** table, with radio button All selected to see all values:

The screenshot shows the 'Data' table with the 'VisitToTubia' column selected. The 'Show Cases' section shows the 'All' radio button selected. The table displays the following data:

Smoker	LungCancer	VisitToTubia	Tuberculosis	Tuberculosis OrCancer	X-ray
s	yes	no	no	yes	yes
)	no	no	no	no	yes
missing>	no	no	no	no	no
)	no	no	no	no	<missing>
s	no	<missing>	no	no	no
s	no	no	no	no	no
)	no	no	no	<missing>	no

Variable	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
VisitToTubia				
no	60	15.96%	60	15.96%
yes	23	6.12%	83	22.07%
<missing>	293	77.93%	376	100.00%
Total	376	100.00%		

To show complete cases, select radio button Complete :

DIONE - Decision Intelligence for Organizations in Network Environments : data file C:\Users\hj_vv\Documents\Dione\data\healthdemomissing.csv

Bayesian Network: Algorithms Learn Structure Fit Parameters

Dashboard Explore Graphical Model

Variables Select All

<filter> #NULL!

Data Clear Highlighted Clear All Show Cases: All Complete Incomplete 32 cases for 8 variab

	Smoker	LungCancer	VisitToTubia	Tuberculosis	Tuberculosis OrCancer	X-ray	Bronchitis	Dyspnea
Smoker	yes	yes	no	no	yes	yes	yes	yes
LungCancer	no	no	no	no	no	yes	yes	yes
VisitToTubia	yes	no	no	no	no	no	yes	yes
Tuberculosis	no	no	no	no	no	no	yes	yes
TuberculosisOrCan...	yes	no	no	no	no	no	yes	yes
X-ray	yes	no	no	no	no	no	yes	yes
Bronchitis	yes	no	no	no	no	no	no	no
Dyspnea	no	no	no	no	no	no	yes	yes
	no	no	no	no	no	no	no	no
	yes	no	no	no	no	no	no	no

You can now also see details on variables for complete cases only by double-clicking in the variable's data column in the **Data** table with the Complete radio button selected:

Smoker	LungCancer	VisitToTubia	Tuberculosis	Tuberculosis OrCancer	X-ray	Bronchitis
yes	yes	no	no	yes	yes	yes
no	no	no	no	no	yes	yes
no	no	no	no	no	no	yes
no	no	no	no	no	no	yes
no	no	no	no	no	no	yes
no	no	no	no	no	no	no

Variable Values	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
VisitToTubia				
no	32	8.51%	32	8.51%
Total	32	8.51%		

Please note that, for numerical variables that have some nonnumerical values, the nonnumerical values will be recoded to missing when selecting radio button Complete or

Incomplete .

Explore Data

Before proceeding to sophisticated data analysis, it is usually a good idea to explore the data with relatively simple tools to develop a better understanding and intuition of their characteristics. With **DIONE** it is simple to explore data by looking at one variable at a time or by comparing two variables (univariate and bivariate methods): frequency tables, bar charts, histograms, scatter plots and calculation of statistics such as mean, median, mode, standard deviation, chi-square tests and risk ratios with p-values, as well as Bayes factors and correlations. To make it easy to decide which variables are most interesting for multivariate analysis, it is also possible to obtain bivariate comparisons between a variable of interest and all other variables and see in one table which variables are likely to be related to the variable of interest. The variable of interest will in many cases be an outcome variable for which you would like to know causes.

One Variable

Select a variable in the **Data** table, by clicking anywhere in its data column, and press button **Calculate Frequencies**, press the Enter key or double-click to see a bar chart and/or histogram and a frequency table of this variable's data at the right of the screen, for example variable **Smoker** with possible values yes and no:

The screenshot shows the DIONE software interface. The main window displays a data table with 10 variables: Smoker, LungCancer, VisitToTubia, Tuberculosis, Tuberculosis OrCancer, X_ray, Bronchitis, Dyspnea, and Age. The 'Smoker' column is highlighted in blue. The 'Calculate Frequencies' button is visible above the data table. To the right, a bar chart and a frequency table for the 'Smoker' variable are displayed.

Variable: Smoker

nr of observations

value

Variable: Smoker

nr of observations

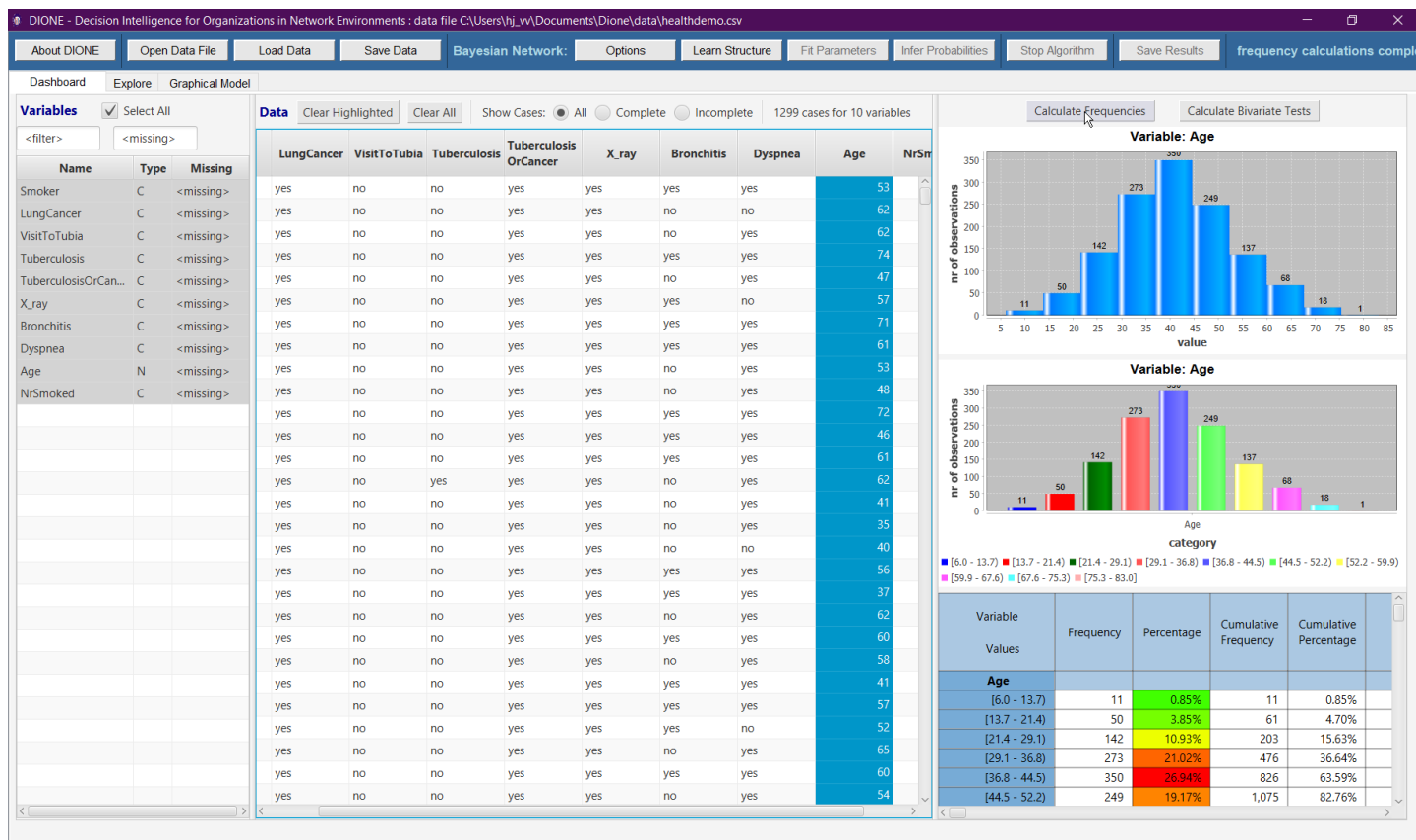
Smoker category

■ no ■ yes

Variable Values	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Smoker				
no	653	50.27%	653	50.27%
yes	646	49.73%	1,299	100.00%
Total	1,299	100.00%		

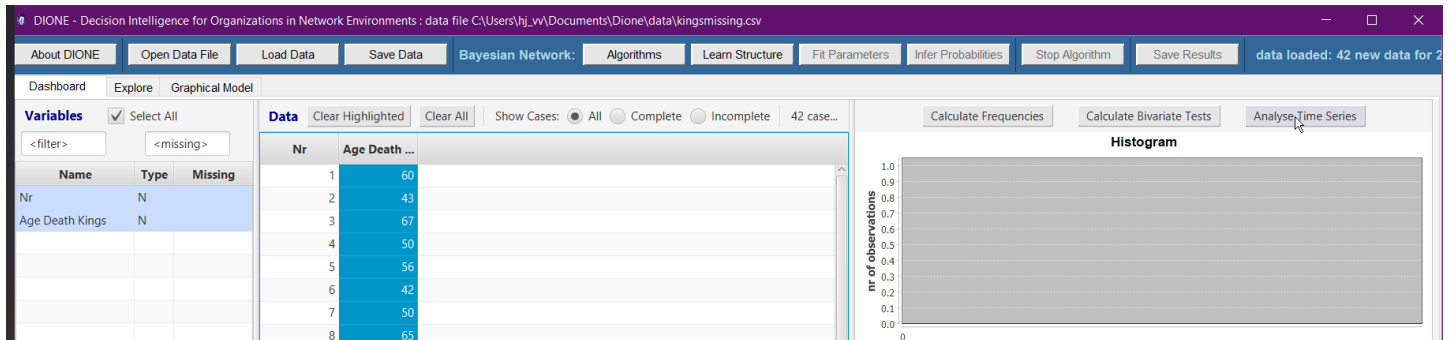
For categorical or ordinal variables, a bar chart is shown. For numerical variables a histogram is shown and under the frequency data in the frequency table their mean, median and standard deviation are shown.

This example from the same data set also shows a histogram for a numerical variable: **Age** (a bar chart is also shown to visualize the raw data):



Time Series Data

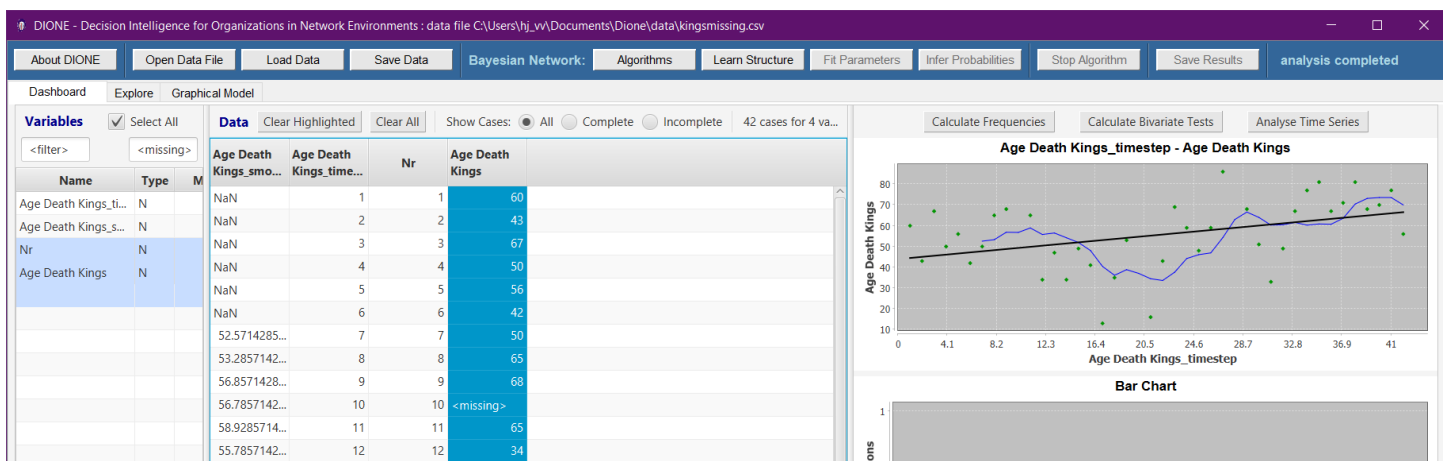
It is also possible to analyse time series data, including smoothing of a time series by calculating a moving average and decomposition of a time series in trend, periodic and random components. As an example we analyse these data on the age of death of successive kings of England by selecting variable **Age Death Kings** in the **Data** table and clicking button **Analyse Time Series** :



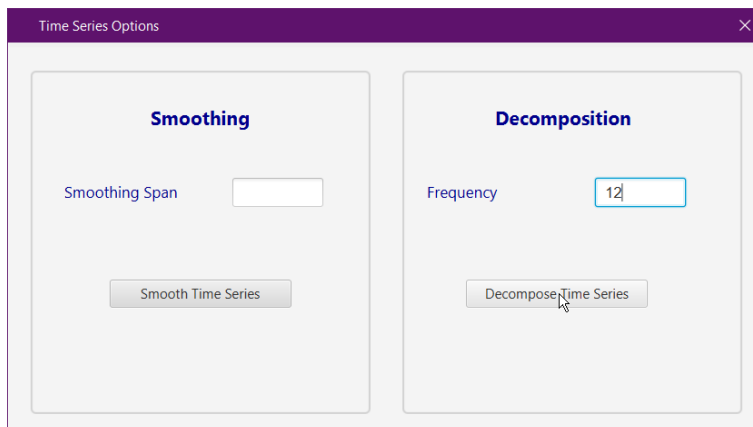
This shows the following dialog. To smooth the time series, set the **Smoothing Span** parameter, which is the number of values to use for a moving average calculation, form example 7 here:

The 'Time Series Options' dialog box is shown with two main sections: 'Smoothing' and 'Decomposition'. In the 'Smoothing' section, the 'Smoothing Span' parameter is set to 7. In the 'Decomposition' section, the 'Frequency' parameter is empty. The 'Smooth Time Series' button is highlighted.

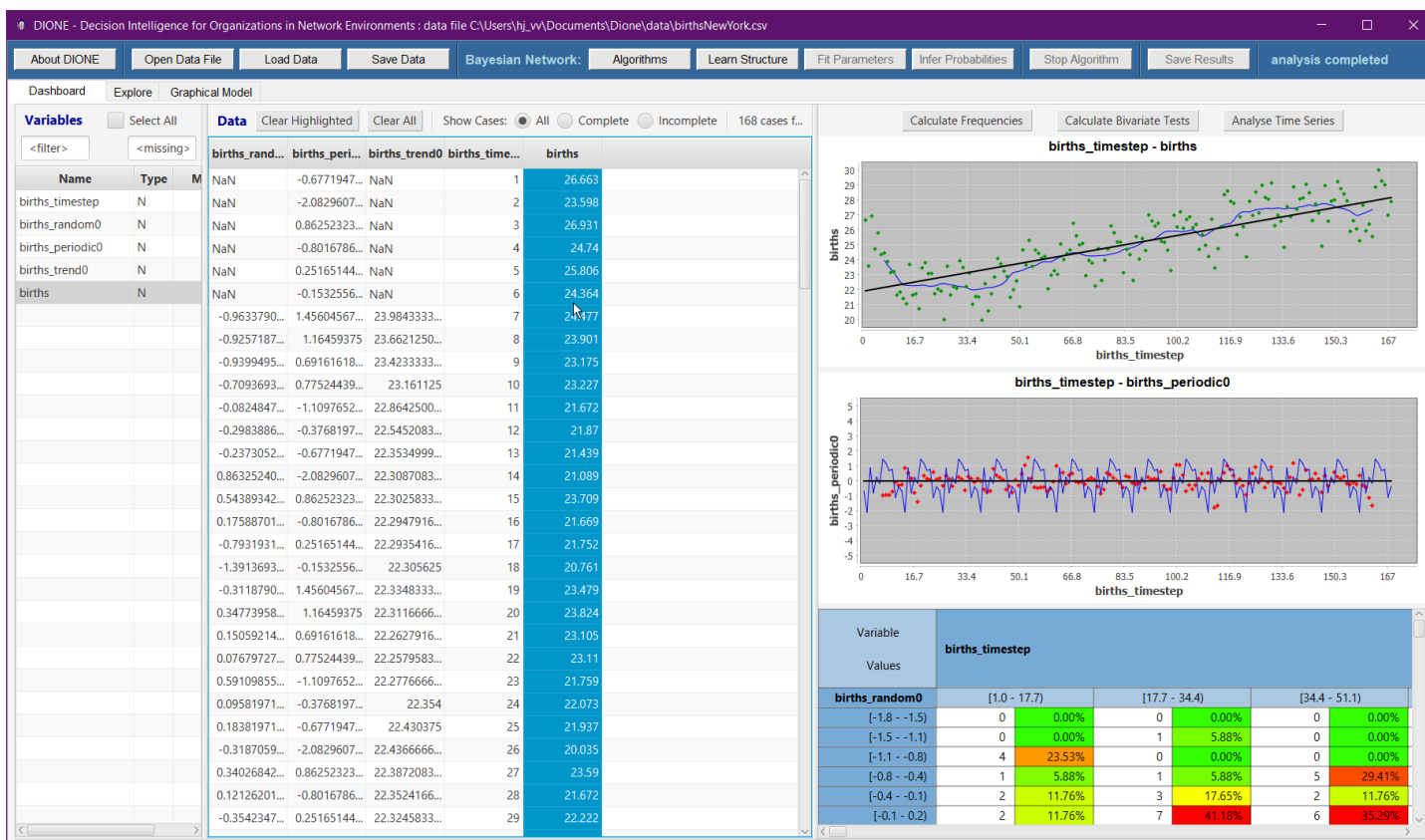
The result is shown here, with data points as dots, the moving average as a blue line and a regression line as a black line:



To decompose a time series, set the **Frequency** parameter, which is the number of values assumed for one period of the time series, for example 12 here for a dataset of monthly births in New York:



The result is shown here, with the top chart showing again data points as dots, the trend component as a blue line and a regression line as a black line, and the bottom chart showing the random component as dots and the periodic component as a blue line:



Two Variables

To compare two variables, select any pair of variables by clicking in the first variable's data column and using Ctrl-click anywhere in the second variable's data column: here **Smoker** (yes/no) and **LungCancer** (yes/no). After pressing button **Calculate Frequencies** or the Enter key, results are shown in the bar chart and in a two-way frequency table, with a preview in the **Dashboard** tab and a more detailed view in the **Explore** tab.

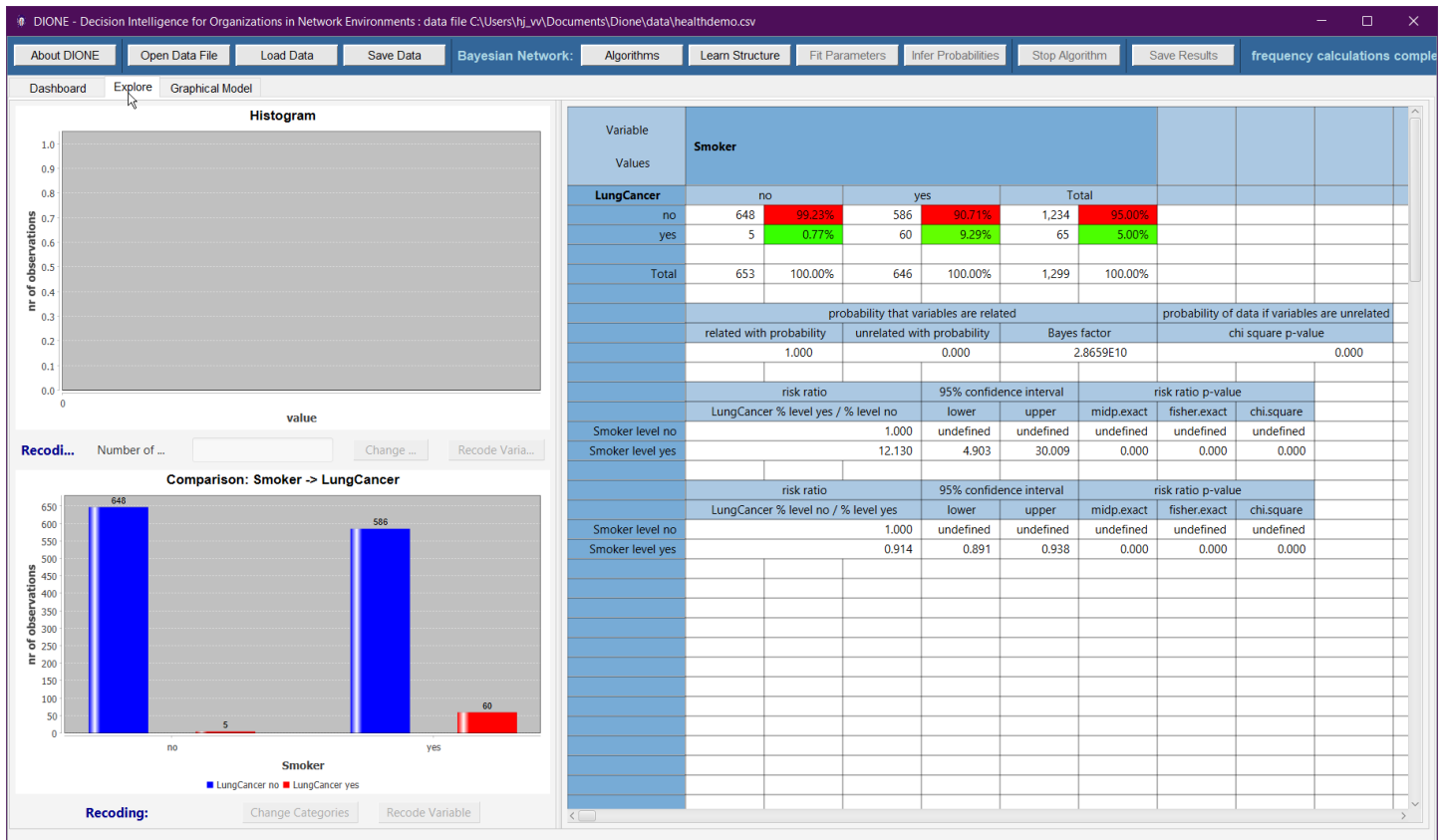
In the frequency table, the chi square p-value indicates the significance of the relation between the variables (the lower the p-value, the more significant). The risk ratio is also calculated with corresponding confidence interval and p-values. The risk ratio (or relative risk) compares the risks for two groups by dividing the incidence in the exposed group by the incidence in the unexposed group. Thus, in the example, the percentage of smokers with lung cancer is 12.13 times the percentage of non-smokers with lung cancer. The risk ratio p-values show that this risk ratio value is significant, and the 95 % confidence interval means that the value is between 4.90 and 30.01 with 95 % probability.

The screenshot shows the DIONE software interface with the following components:

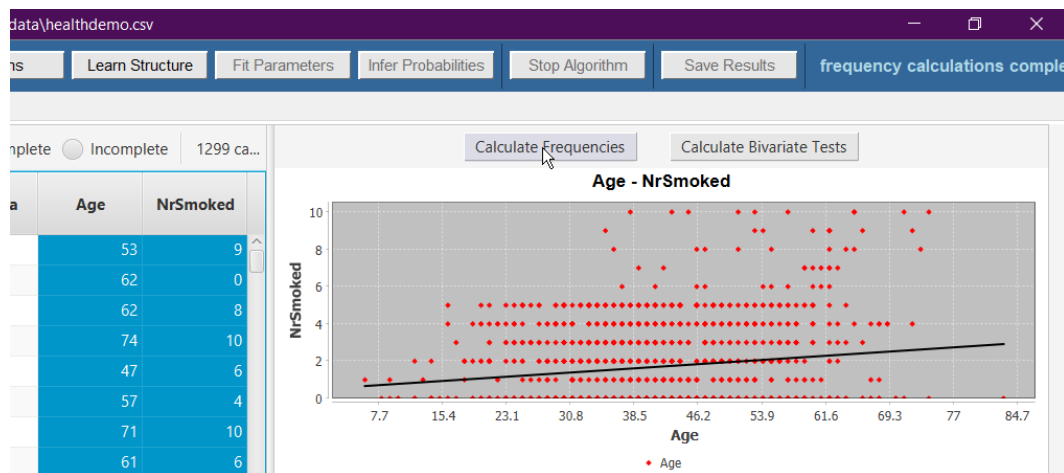
- Dashboard:** Includes tabs for 'About DIONE', 'Open Data File', 'Load Data', 'Save Data', 'Bayesian Network', 'Algorithms', 'Learn Structure', 'Fit Parameters', 'Infer Probabilities', 'Stop Algorithm', 'Save Results', and 'frequency calculations complete'.
- Variables Panel:** Lists variables like Smoker, LungCancer, VisitToTubia, Tuberculosis, TuberculosisOrCancer, X_ray, and Bronchitis. The 'Smoker' variable is selected.
- Data Table:** A grid showing individual data points for the selected variables. The 'Smoker' and 'LungCancer' columns are highlighted in blue.
- Calculate Frequencies:** A button that triggers the analysis.
- Histogram:** A plot showing the distribution of values for the selected variables.
- Comparison: Smoker -> LungCancer:** A bar chart comparing the number of observations for 'no' and 'yes' smokers, further broken down by 'LungCancer' status (no in blue, yes in red).
- Frequency Table:** A 2x2 contingency table showing the relationship between Smoker and LungCancer.

Variable	Smoker		Total	
Values	no	yes		
LungCancer	no	yes	Total	
no	648	586	1,234	99.23%
yes	5	60	65	0.77%
				9.29%
Total	653	646	1,299	100.00%

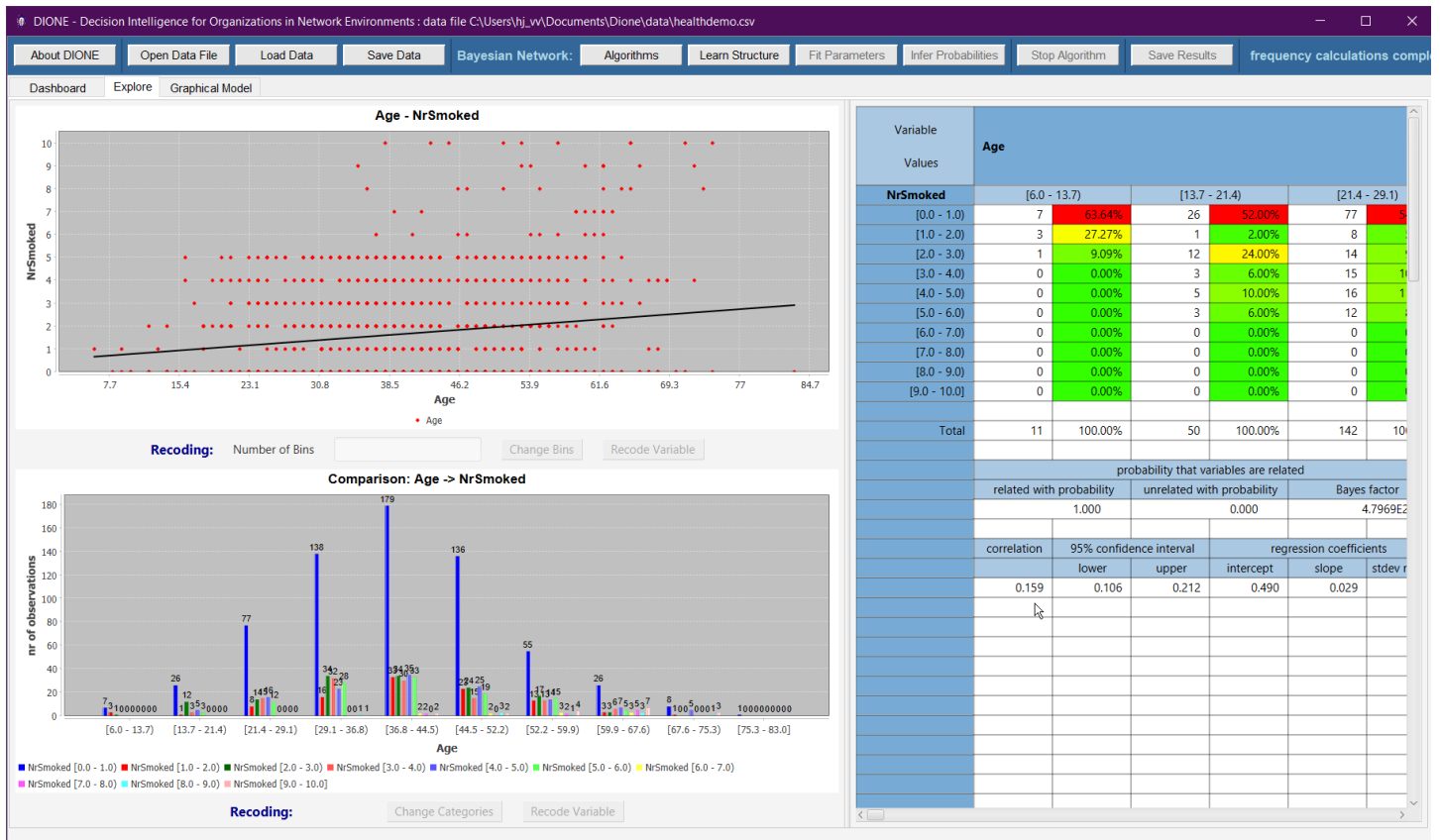
probability that variables are related



Frequencies can also be calculated for two numerical variables, for example **Age** and **NrSmoked**, after setting **NrSmoked** to **Type** numerical (N) in the **Variables** table. As shown here, they are compared in a scatter plot, including a linear line of best fit (regression line):

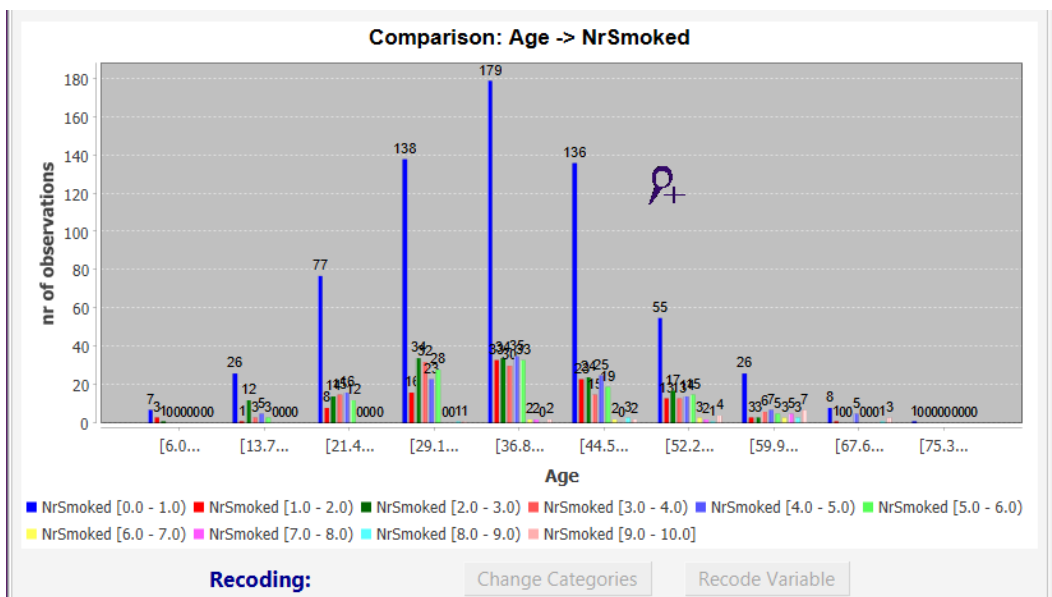


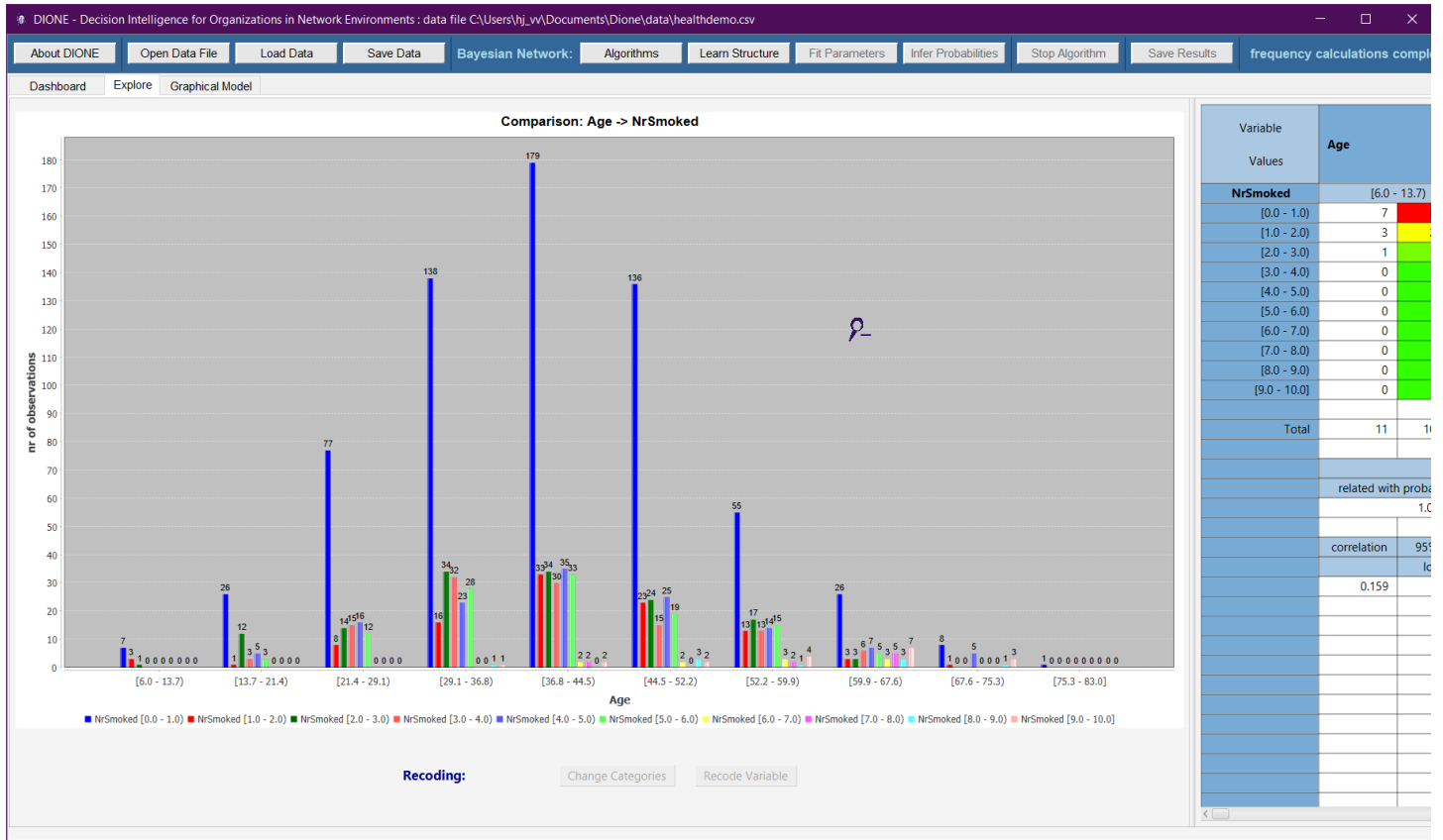
Their correlation coefficient is shown in the results table after the frequency data. Correlation coefficient 1 means perfect correlation and 0 means no correlation, so in the example there is a weak correlation, as is also clear from the scatter plot. Regression coefficients are also shown.



Inspect Results

A preview of results is shown in the **Dashboard** tab and a more detailed view in the **Explore** tab. Sometimes a variable has many levels and/or long texts as values, so the chart become hard to read. In the **Explore** tab you can zoom in on a chart by hovering over it with the mouse to show an hourglass with a + sign, then clicking to zoom in:





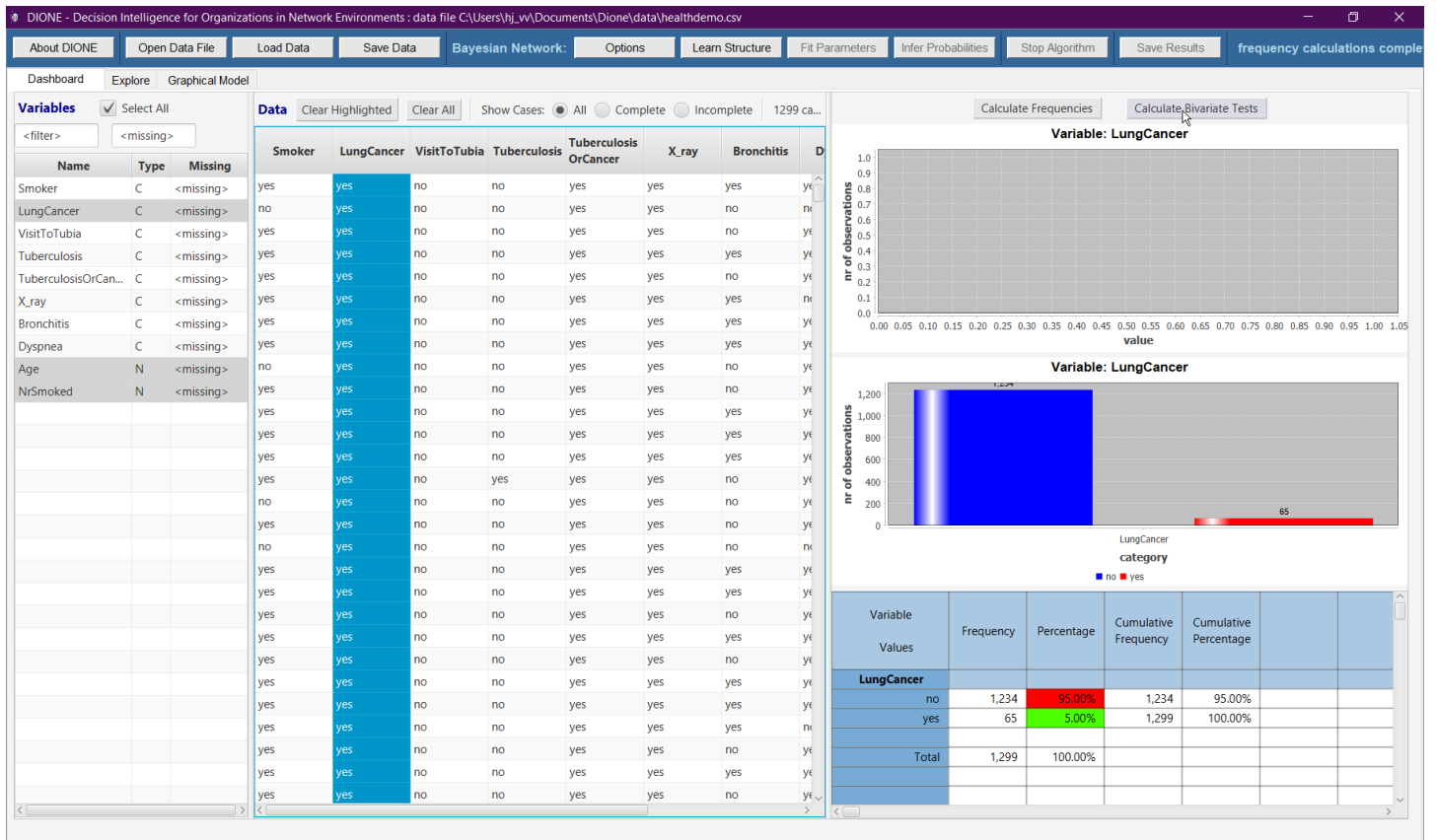
The hourglass now has a – sign to zoom out again.

At the right-hand side of the **Explore** tab, there is a table with detailed frequency data and other analysis results. For numerical variables, frequencies of ranges of values are shown. If desired, you can get more details about individual values of a variable by right-clicking on one of the value ranges in the left-hand column and choosing menu item **Inspect Data** to see the distinct values of that variable:

Variable	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Age				
[6.0 - 13.7]	11	0.85%	11	0.85%
[13.7 - 21.4]	50	3.85%	61	4.70%
[21.4 - 29.1]	142	10.93%	203	15.63%
[29.1 - 36.8]	173	21.02%	476	36.64%
[36.8 - 44.5]	150	26.94%	826	63.59%
[44.5 - 52.2]	149	19.17%	1,075	82.76%
[52.2 - 59.9]	137	10.55%	1,212	93.30%
[59.9 - 67.6]	68	5.23%	1,280	98.54%
[67.6 - 75.3]	18	1.39%	1,298	99.92%
[75.3 - 83.0]	1	0.08%	1,299	100.00%
Total	1,299	100.00%		

All Variables

To obtain bivariate comparisons of one variable with other variables, start by selecting, in the **Dashboard** tab, one variable as the outcome variable of interest. In this example the outcome variable is **LungCancer**, with which all other loaded variables will be compared:



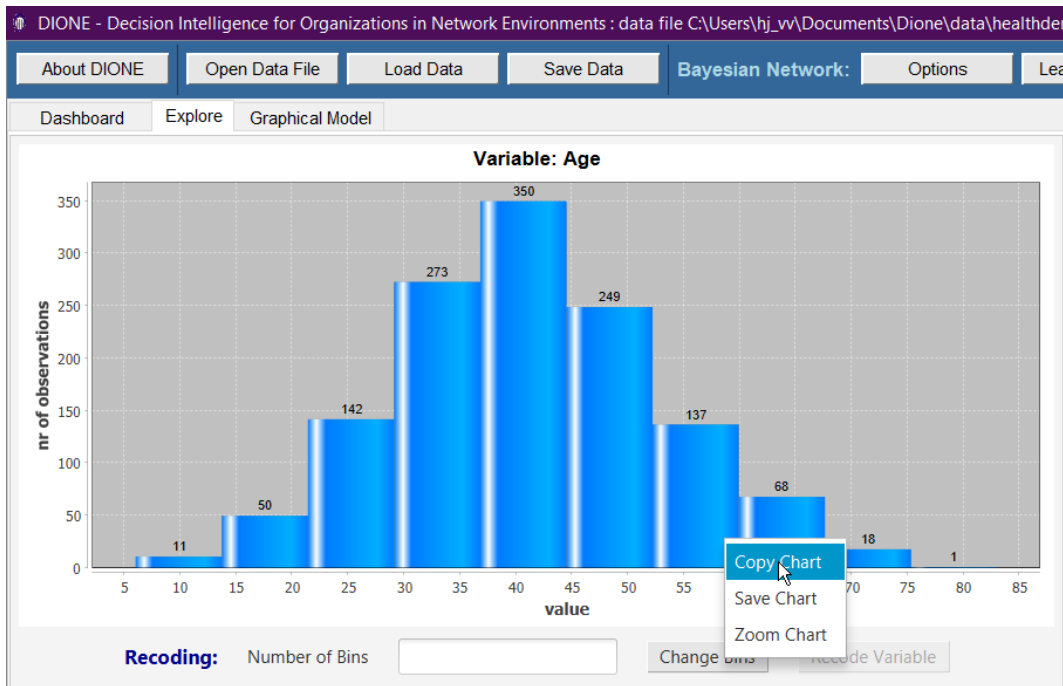
Press button **Calculate Bivariate Tests** above the plots (histogram and bar chart) at the right.

Go to the **Explore** tab and scroll to the right in the results table to see the p-values of chi square tests of the selected outcome variable compared with all other loaded variables, ordered from most to least significant association. This allows you to see quickly which variables have the most significant association with the selected outcome variable and so are likely to be of interest for further analysis. In the example all variables except **Bronchitis** and **VisitToTubia** have significant associations at the 1 % (so also of course at the 5 %) significance level with **LungCancer** ($p < 0.01$ and $p < 0.05$).

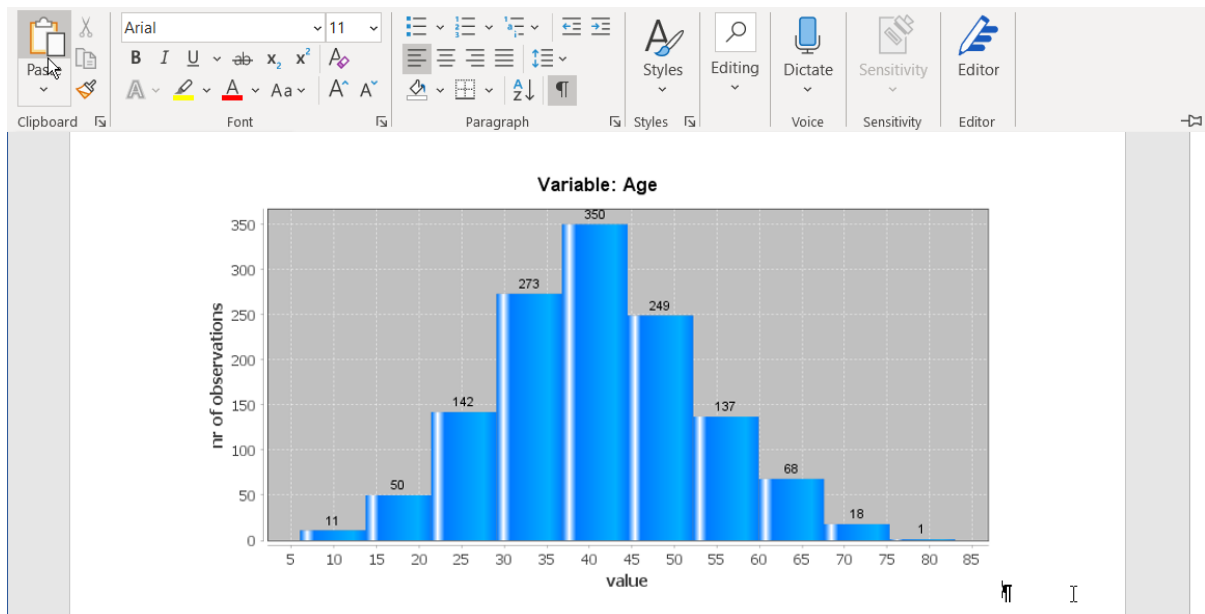
Copy and Save Results

You can keep your results by copying charts and tables to another application, for example to insert them in a word processing document, or by saving them to a file.

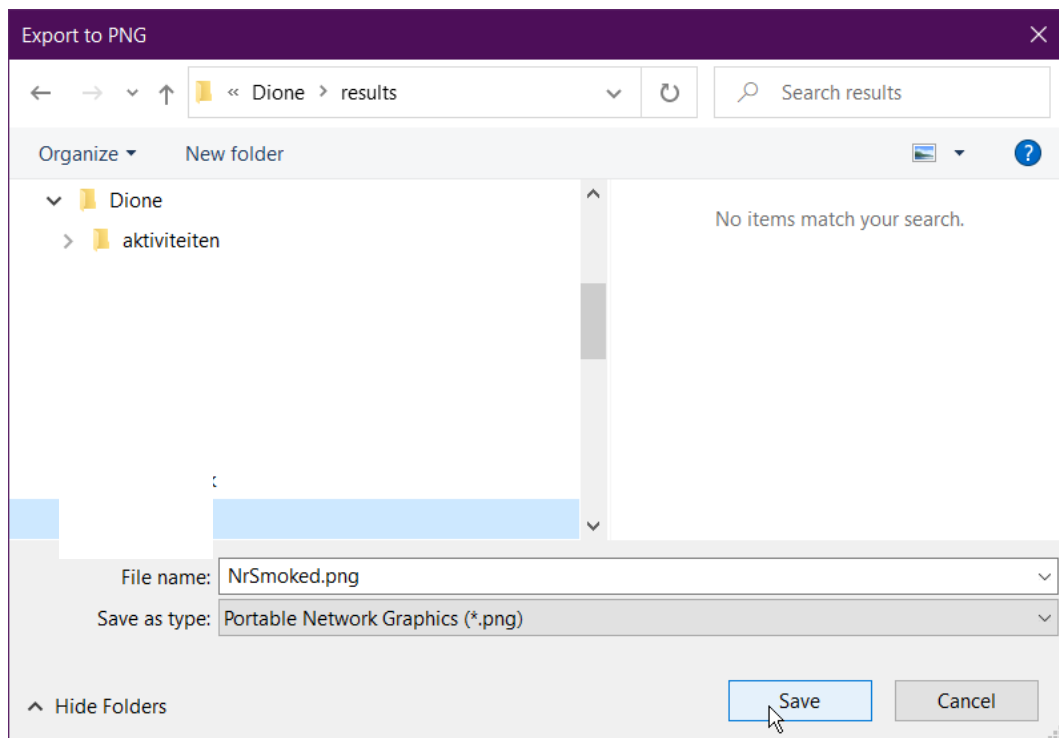
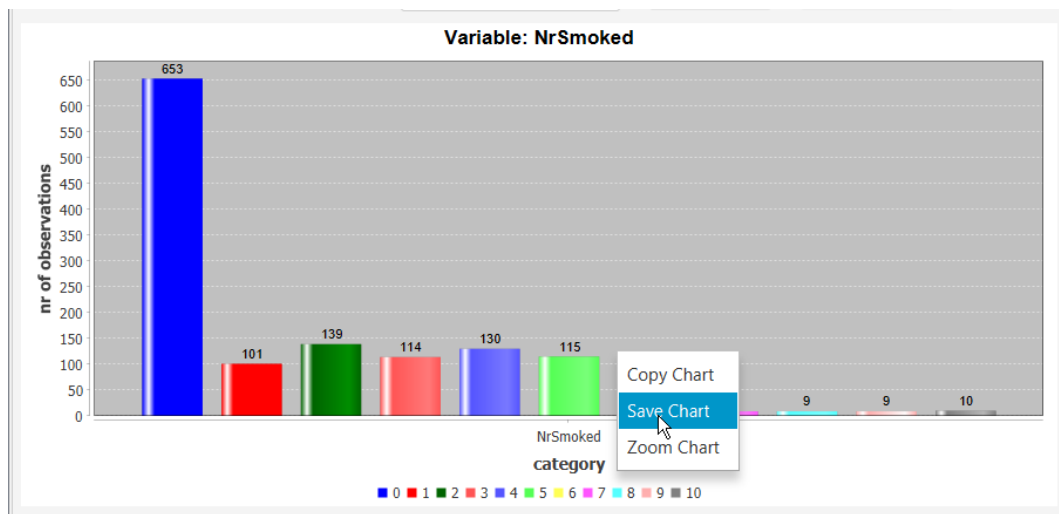
To copy a bar chart or a histogram, right-click on it and select **Copy Chart** from the pop-up menu to put a picture of the chart on your computer's clipboard:



You can now paste the picture in a Word document, for example:



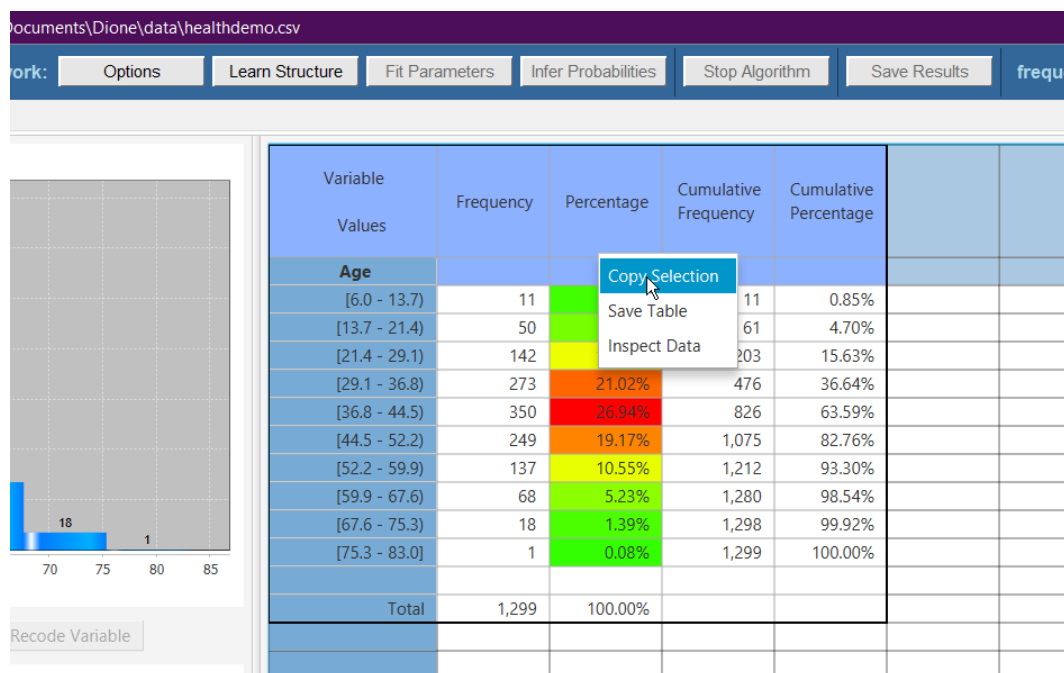
To save a chart to a file, right-click on it and select **Save Chart** from the pop-up menu to open a save dialog:



You now have a Portable Network Graphics (PNG) picture file that you can open in any image processing program or insert in a document.

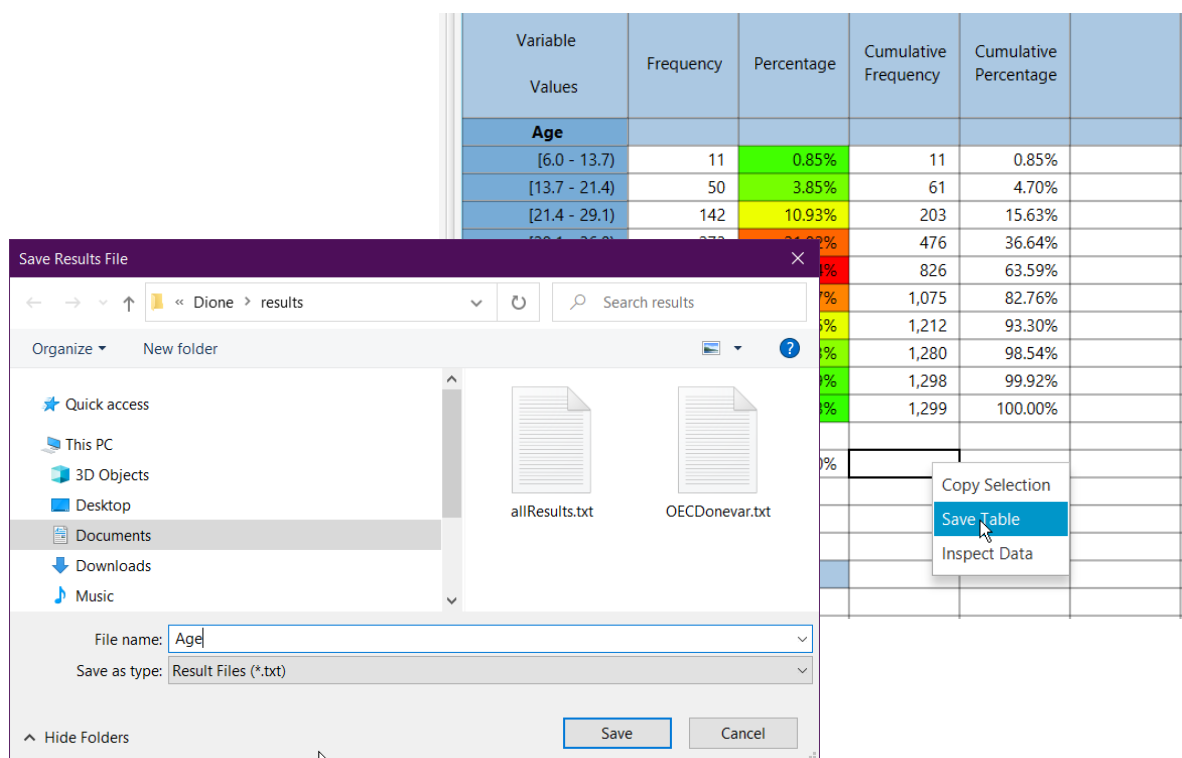
There is another option, **Zoom Chart**, in the pop-up menu that you can use to zoom in or out a chart as with the zoom hourglass, if you prefer.

You can copy results in the frequency table by right-clicking on a selection of data you want to copy and choosing **Copy Selection** in the pop-up menu:



Copied data can be pasted in a Word document, for example, in the same way as described for a chart.

You can save the whole table in a text file by right-clicking anywhere in the table and choosing **Save Table** in the pop-up menu to bring up a save dialog:

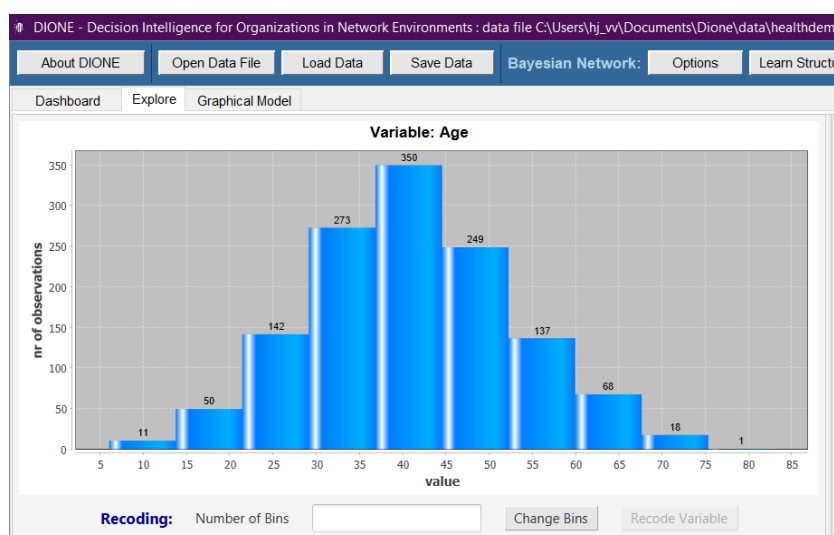


Recode Data

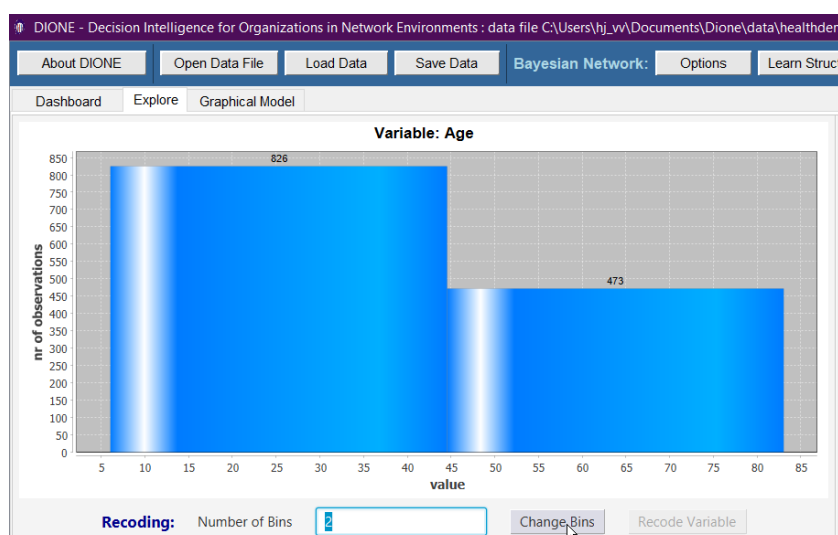
When a variable has numerical data, sometimes more meaningful results can be obtained by recoding it to categorical data. An example is variable **Age** in the second example of the **Explore Data** section. You can recode such variables to categorical variables in the **Explore** tab. You can also recode categorical variables to new categorical variables with different categories, typically to reduce the number of categories or to give categories meaningful names. Recoding a variable does not replace the existing variable but creates a new variable with a new name.

Numerical to Categorical

For example, we would like to recode the variable **Age**, which has values from 6 to 83 years old, to a variable with two categories (age groups). When **Age** is selected in the **Dashboard** tab, the **Explore** tab shows this histogram:



Type the value 2 in the **Number of Bins** text field and press Enter to organize the **Age** data in two categories. The cut-off point between the two categories is automatically made:



Category borders can be changed by pressing button **Change Bins** to open the recoding dialog, in which the recoded variable name and its category names can also be changed:

Recode Numerical Variable

Variable Name: Age Recoded Variable Name: Age_recoded1

Number of Bins: 2

Minimum: 6.0

Maximum: 83.0

>= start border	< end border	category
6.0	44.5	6-44
44.5	83.0	45-83

End border values are in next bin. Only maximum value is always in last bin.
End numbers in proposed category names are approximate.

Recode Numerical Variable

Variable Name: Age Recoded Variable Name: Age_2groups

Number of Bins: 2

Minimum: 6.0

Maximum: 83.0

>= start border	< end border	category
6.0	35	6-34.999
35	83.0	35-82.999

End border values are in next bin. Only maximum value is always in last bin.
End numbers in proposed category names are approximate.

Cancel OK

In the **Recoded Variable Name** field a name is proposed for the new variable, which you can accept or change to a name you prefer. The new name cannot be the name of an existing variable; if the name is already in use, an error message is shown. In the **< end border** column of the **Bins** table, type the desired cut-off value(s) (the cut-off value itself will be in the next higher bin), then press OK. Values in the table are easily edited by using arrow keys to change rows: for example, immediately after editing a cell, use the Down Arrow key to edit the cell below.

This will create a new variable with the new name, with two categories (<35 and ≥35) and show it in the **Dashboard** tab, where the new variable appears at the top of the **Variables** table and in the first column of the **Data** table.

Press button **Calculate Frequencies** , press the Enter key or double-click in the new variable column to see its data:

The screenshot displays the DIONE software interface. The main window shows a data table with columns: Age_2groups, Smoker, LungCancer, VisitToTubia, Tuberculosis, Tuberculosis OrCancer, X_ray, and Bron. The 'Age_2groups' column is highlighted in blue. To the right, there are two visualizations: a histogram and a bar chart. The histogram shows the distribution of 'Age_2groups' values. The bar chart shows the frequency of observations for 'Age_2groups' with two categories: 6-34 (blue bar, 377 observations) and 35-83 (red bar, 922 observations). Below the bar chart is a summary table for 'Age_2groups'.

Variable	Values	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Age_2groups	6-34	377	29.02%	377	29.02%
	35-83	922	70.98%	1,299	100.00%
	Total	1,299	100.00%		

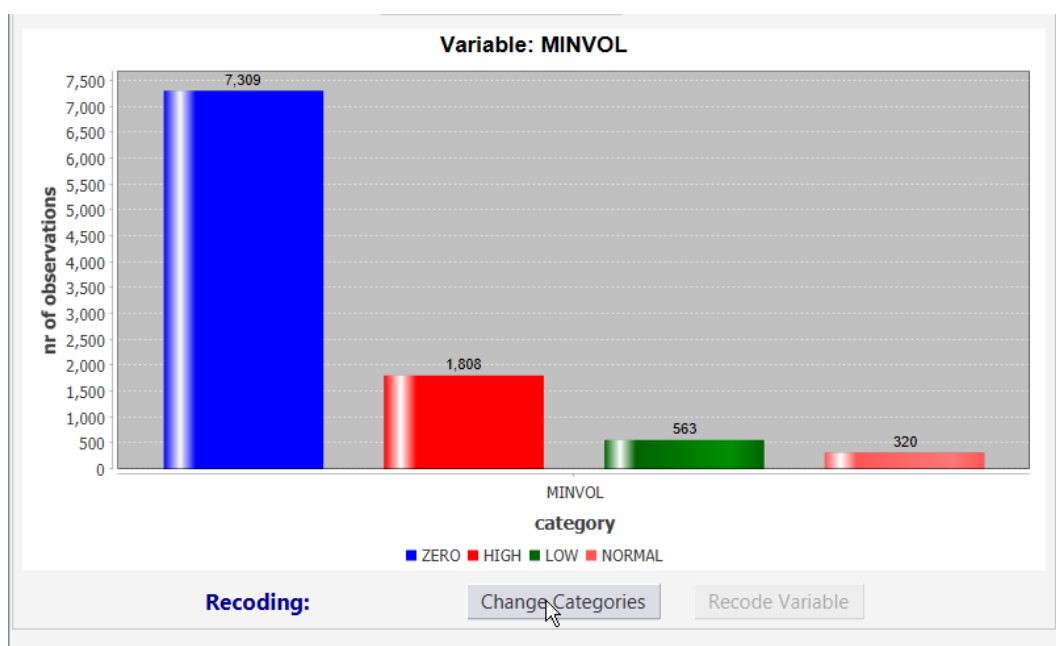
Categorical to Categorical

An example of recoding a categorical variable to a new categorical variable with different categories is variable **MINVOL** from data file alarm.csv. When **MINVOL** is selected in the **Dashboard** tab and its frequencies are displayed (**Calculate Frequencies** , Enter key or double-click),

The screenshot shows the DIONE software interface. The **Dashboard** tab is active, and the **MINVOL** variable is selected. The **Calculate Frequencies** button is highlighted. The frequency distribution for **MINVOL** is shown in a bar chart and a table below it.

Variable Values	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
MINVOL				
ZERO	7,309	73.09%	7,309	73.09%
HIGH	1,808	18.08%	9,117	91.17%
LOW	563	5.63%	9,680	96.80%
NORMAL	320	3.20%	10,000	100.00%
Total	10,000	100.00%		

the **Explore** tab shows this bar chart:



Now press button **Change Categories** to map the existing categories of the variable to the desired new categories and optionally give a new name for the recoded variable:

Recode Categorical Variable

Variable Name: MINVOL Recoded Variable Name: MINVOL_recoded1

old category	new category	order
HIGH	HIGH	
LOW	LOW	
NORMAL	NORMAL	
ZERO	ZERO	

Recode Categorical Variable

Variable Name: MINVOL Recoded Variable Name: MINVOL_positivezero

old category	new category	order
HIGH	POSITIVE	1
LOW	POSITIVE	2
NORMAL	POSITIVE	3
ZERO	ZERO	4

Cancel OK

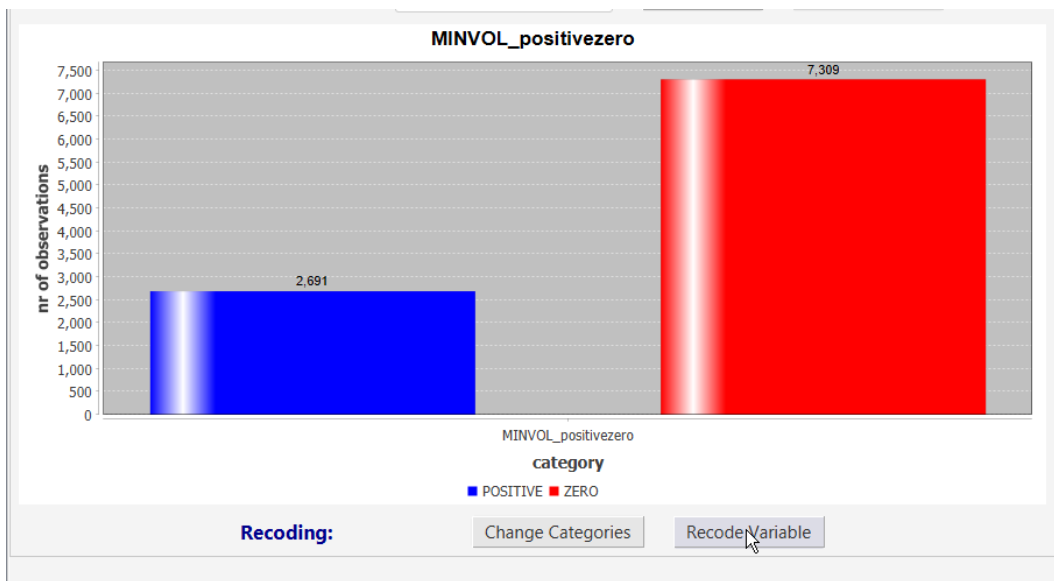
Recode Categorical Variable

Variable Name: MINVOL Recoded Variable Name: MINVOL_positivezero

old category	new category	order
HIGH	POSITIVE	1
LOW	POSITIVE	2
NORMAL	POSITIVE	3
ZERO	ZERO	4

Cancel OK

When you are satisfied with the proposed recoding, press button **Recode Variable** next to the **Change Categories** button to actually create the new recoded variable:



This will create a new variable with the new name, with two categories (POSITIVE and ZERO), and show it in the **Dashboard** tab, where it appears at the top of the **Variables** table and in the first column of the **Data** table. Press button **Calculate Frequencies**, the Enter key or double-click in the new variable column to see its data:

The screenshot shows the DIONE software interface. The top menu bar includes "About DIONE", "Open Data File", "Load Data", "Save Data", "Bayesian Network:", "Options", "Learn Structure", "Fit Parameters", "Infer Probabilities", "Stop Algorithm", "Save Results", and a "100%" progress indicator. The main interface is divided into several sections:

- Dashboard**: Includes "Explore" and "Graphical Model" tabs.
- Variables**: A table listing various variables with columns for "name", "type", and "missing".
- Data**: A table showing the data for the selected variable "MINVOL_positvezero". The first column contains the categories "POSITIVE" and "ZERO".
- Histogram**: A histogram showing the distribution of observations for the variable "MINVOL_positvezero". The y-axis is "nr of observations" (0 to 7,000) and the x-axis is "value" (category). The blue bar for "POSITIVE" has a value of 2,691 and the red bar for "ZERO" has a value of 7,309.
- Calculate Frequencies**: A table showing the frequency and percentage of observations for each category.

Variable	Values	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
MINVOL_positvezero	POSITIVE	2,691	26.91%	2,691	26.91%
	ZERO	7,309	73.09%	10,000	100.00%
	Total	10,000	100.00%		

Learn Bayesian Networks

In the **Dashboard** tab, ensure that the variables you want to analyse are selected in the **Variables** table and, by pressing the **Load Data** button or the Enter key, loaded and shown in the **Data** table. If you want to change the variables to analyse, change the selected variables as explained under **Load Data**.

Learn Network Structure

Now press button **Learn Structure** to learn a Bayesian network structure from the selected data.

The screenshot shows the DIONE software interface. The top menu bar includes 'About DIONE', 'Open Data File', 'Load Data', 'Save Data', 'Bayesian Network:', 'Options', 'Learn Structure', 'Fit Parameters', 'Infer Probabilities', and 'Stop Algorithm'. The 'Learn Structure' button is highlighted. Below the menu, there are tabs for 'Dashboard', 'Explore', and 'Graphical Model'. The 'Data' table is displayed with the following columns: Smoker, LungCancer, VisitToTubia, Tuberculosis, Tuberculosis OrCancer, X_ray, Bronchitis, Dyspnea, Age, and NrSmoked. The table contains 1299 cases for 10 variables.

name	type	missing	Smoker	LungCancer	VisitToTubia	Tuberculosis	Tuberculosis OrCancer	X_ray	Bronchitis	Dyspnea	Age	NrSmoked
Smoker	C	<missing>	yes	yes	no	no	yes	yes	yes	yes	53	9
LungCancer	C	<missing>	no	yes	no	no	yes	yes	no	no	62	0
VisitToTubia	C	<missing>	yes	yes	no	no	yes	yes	no	yes	62	8
Tuberculosis	C	<missing>	yes	yes	no	no	yes	yes	yes	yes	74	10
Tuberculosis Or...	C	<missing>	yes	yes	no	no	yes	yes	no	yes	47	6
X_ray	C	<missing>	yes	yes	no	no	yes	yes	yes	no	57	4
Bronchitis	C	<missing>	yes	yes	no	no	yes	yes	yes	yes	71	10
Dyspnea	C	<missing>	yes	yes	no	no	yes	yes	yes	yes	61	6
Age	N	<missing>	no	yes	no	no	yes	yes	no	yes	53	0
NrSmoked	C	<missing>	yes	yes	no	no	yes	yes	no	yes	48	4
			yes	yes	no	no	yes	yes	yes	yes	72	9
			yes	yes	no	no	yes	yes	yes	yes	46	8

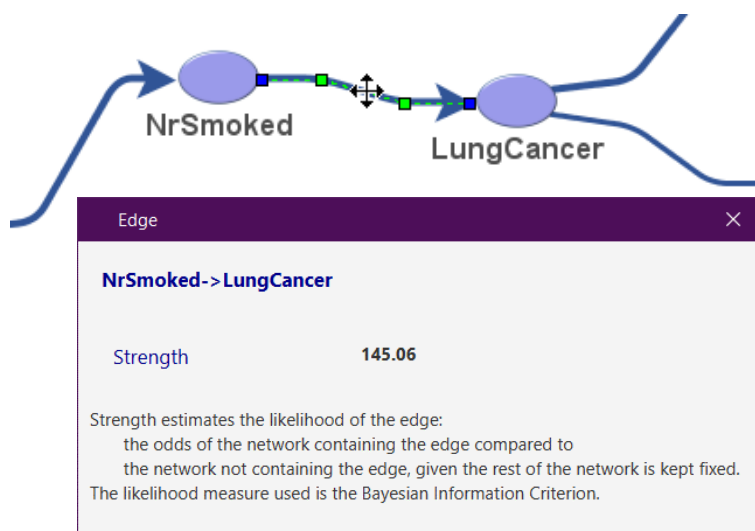
The result should look something like this in the **Graphical Model** tab:

The screenshot shows the DIONE software interface with the 'Graphical Model' tab selected. The diagram illustrates a Bayesian network with nodes representing variables: Smoker, Tuberculosis, NrSmoked, LungCancer, Age, Bronchitis, TuberculosisOrCancer, X_ray, Dyspnea, and VisitToTubia. The nodes are connected by directed edges representing causal relationships. The 'Age' node is highlighted in green. The interface includes a 'Zoom Graph' section with a 100% zoom level and a 'Copy Graph' button.

In the learned Bayesian network, nodes represent variables and arrows represent possible causal relations between variables. Directed lines, with arrows, represent possible causal relations including the direction of causality, while any undirected lines, without arrows, represent possible causal relations with unspecified causal direction. If there is no significant association between two variables, there is no line between their nodes. The default structure learning algorithm, tabu search, produces a directed graph with only arrows.

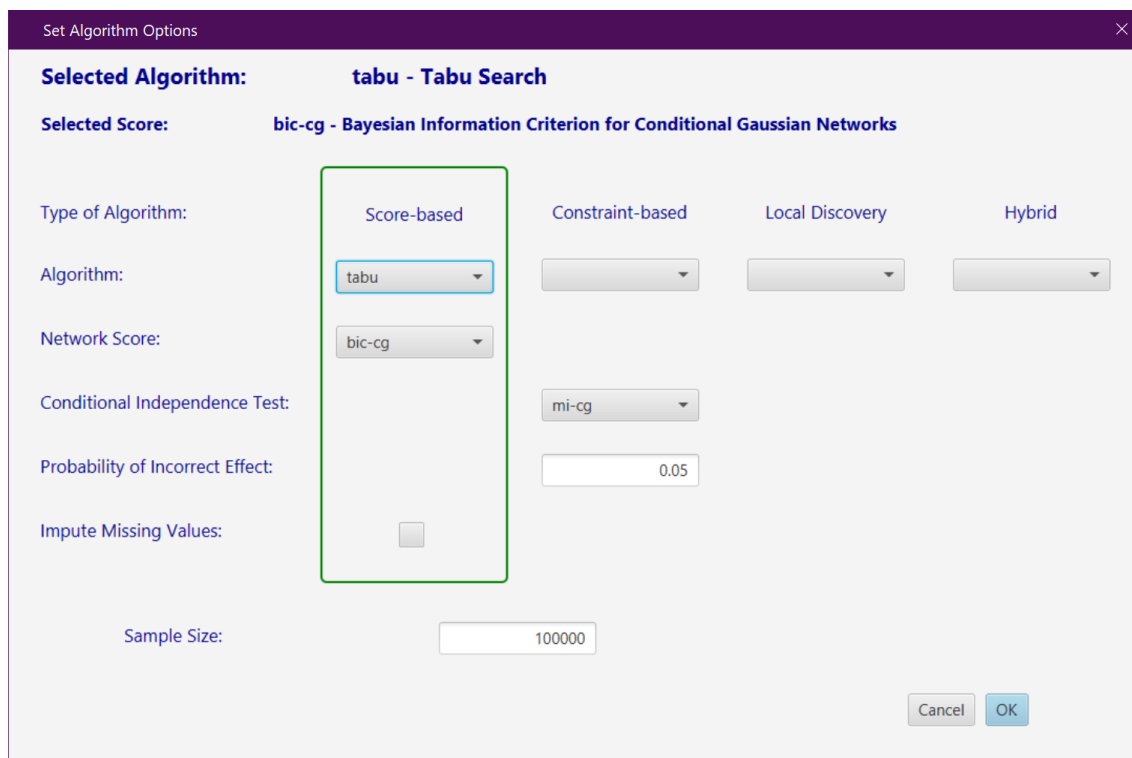
The algorithm also calculates edge strengths. The strength of an edge estimates the likelihood of the edge: the odds of the network containing the edge compared to the network not containing the edge, given the rest of the network is kept fixed. The likelihood measure used is the Bayesian Information Criterion.

Edge strengths are indicated by the thickness and colour of the arrows. The thicker an arrow, the stronger is the evidence for the causal connection. Edge strengths can be inspected by right-clicking on an arrow:



In this example the strength of the connection between **NrSmoked** and **LungCancer** is over 145, indication that the network with this connection is much more likely than a network without the connection and otherwise the same.

The default structure learning algorithm is tabu search, but other structure learning algorithms can be used by selecting one in the **Set Algorithm Options** dialog accessed by pressing the **Algorithms** button:



DIONE uses the R package bnlearn for structure learning and parameter fitting. Supported structure learning algorithms are described in the [bnlearn manual](#) on pages 100 – 102 at bookmark structure-learning. Structure learning algorithms can be Score-based, Constraint-based, Local Discovery or Hybrid algorithms. To use a specific algorithm, select it in the Algorithm drop down list under the relevant category.

Score-based algorithms use a network score to compare solutions. Possible network scores are described in the [bnlearn manual](#) on pages 81 – 82 at bookmark network-scores. To use a specific score, select it in the Network Score drop down list.

Constraint-based algorithms and Local Discovery algorithms use a conditional independence test to find solutions. Possible tests are described in the [bnlearn manual](#) on pages 66 – 67 at bookmark independence-tests. To use a specific test, select it in the Conditional Independence Test drop down list.

Hybrid algorithms use a network score as well as a conditional independence test. When a Hybrid algorithm is selected in the Algorithm drop down list under Hybrid, the algorithm uses the Network Score selected under Score-based and the Conditional Independence Test selected under Constraint-based. When the rsmx2 Hybrid algorithm is selected, it combines the algorithms selected under Score-based and under Constraint-based.

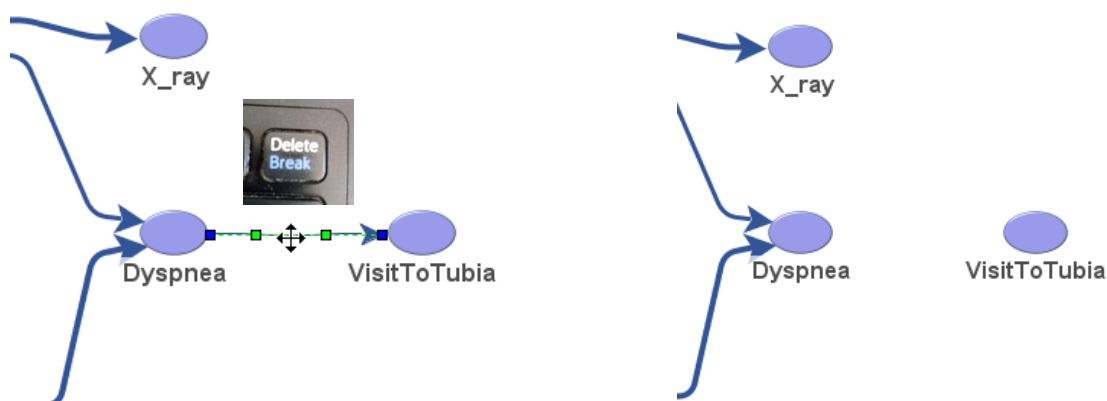
Edit Network Structure

The next step in the analysis will be the parameter fitting algorithm, which calculates detailed information for all nodes and arrows, such as conditional probabilities and/or regression coefficients quantifying the causal relationships between variables. Before continuing with parameter fitting, you may wish to edit the network structure to reflect knowledge or intuition you already have about causal connections between variables. You can move or delete nodes, add or delete arrows or reverse their direction.

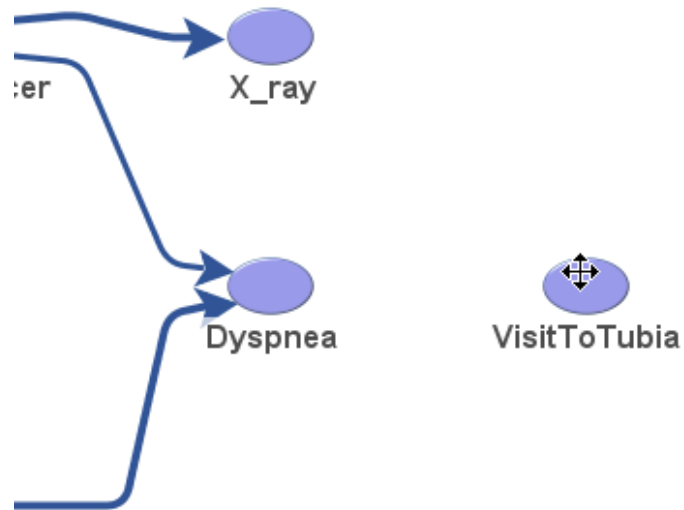
Adding an arrow or changing direction of an arrow can possibly result in a red arrow, meaning that a network with that connection is less likely than a network without it.

For example, in the learned network shown on page 20 the arrow between variables **Dyspnea** and **VisitToTubia** does not seem to reflect a likely causal connection. Let us say we want to remove it and instead postulate a causal connection between **VisitToTubia** and **Tuberculosis**.

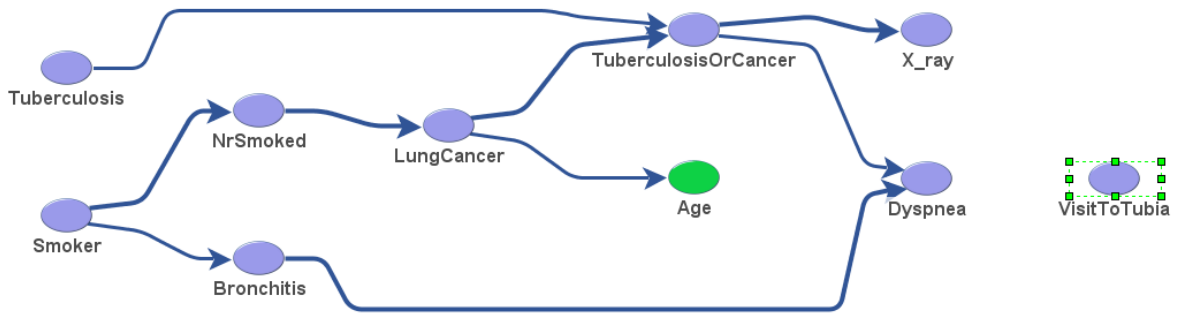
First, we delete the arrow between **Dyspnea** and **VisitToTubia** with the Delete key:



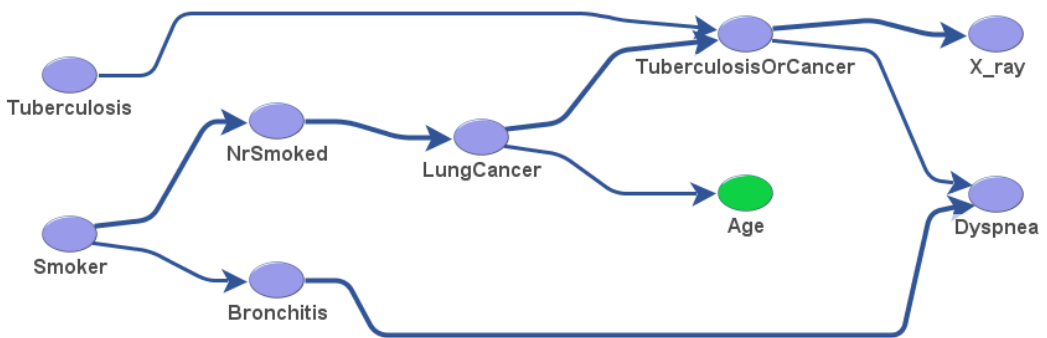
Now, to keep the diagram tidy, we move the node of variable **VisitToTubia** to a position near the **Tuberculosis** node. To move a node, hover over it with the mouse to show a black cross and drag it to the desired location:



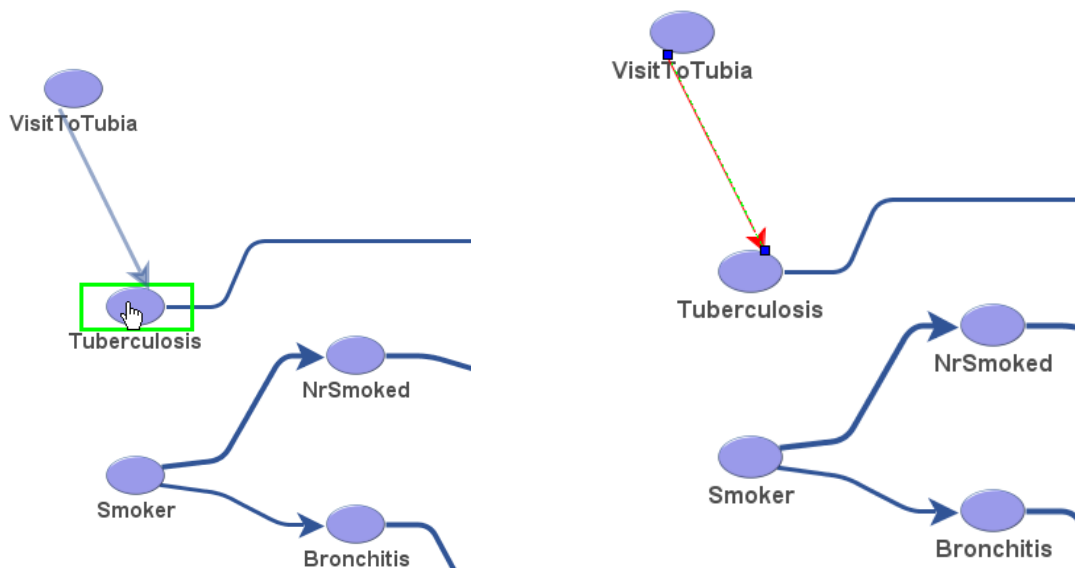
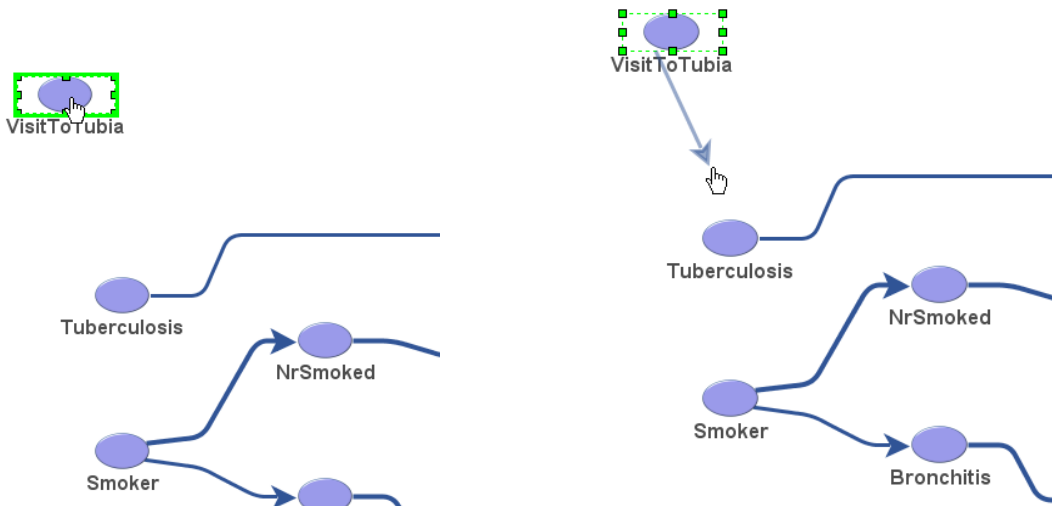
VisitToTubia



VisitToTubia

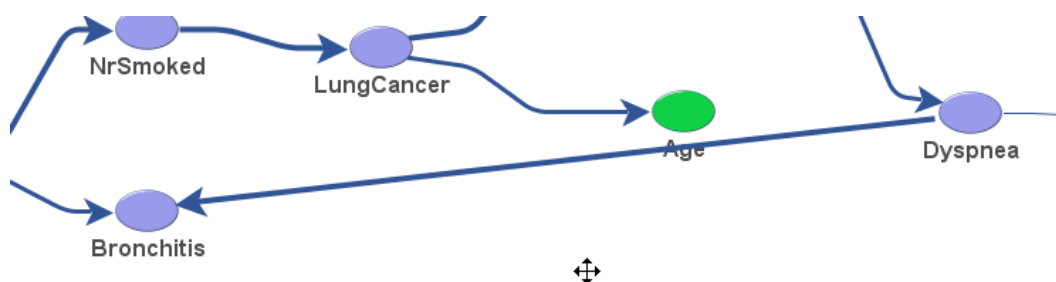
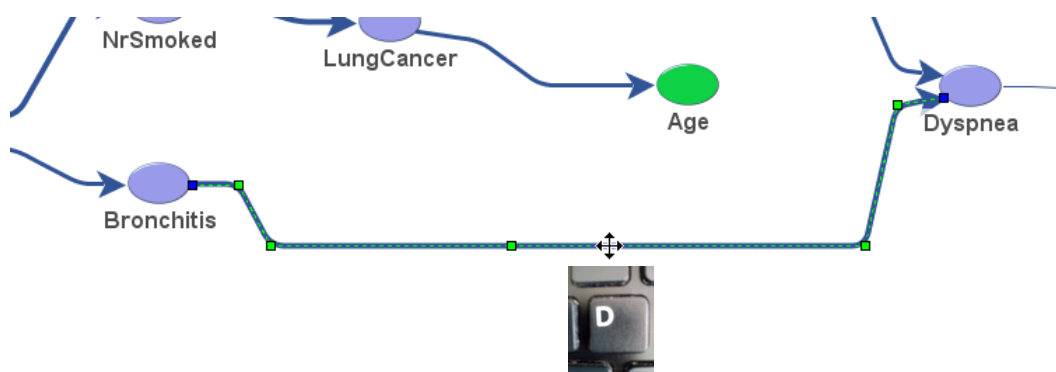


To add a new arrow between the two nodes **VisitToTubia** and **Tuberculosis**, first hover with the cursor over the node that is considered the cause (**VisitToTubia**) and where the arrow is to start, such that the cursor is a hand and there is a green frame around the node. Now press the left mouse button and, while holding it, move the mouse to draw an arrow to the node that is considered the effect (**Tuberculosis**) and where the arrow is to end. When there is a green frame around the effect node, release the mouse button. The new arrow has now been added:



Note that the arrow between nodes **VisitToTubia** and **Tuberculosis** , which has been manually added, is red, meaning that the causal relationship between variables **VisitToTubia** and **Tuberculosis** is not likely, given the data.

You can also reverse the direction of directed arrows if their direction does not make sense to you, or to eliminate cycles. To reverse the direction of an arrow, select it by clicking on the line of the arrow and push the **D** key on your keyboard:



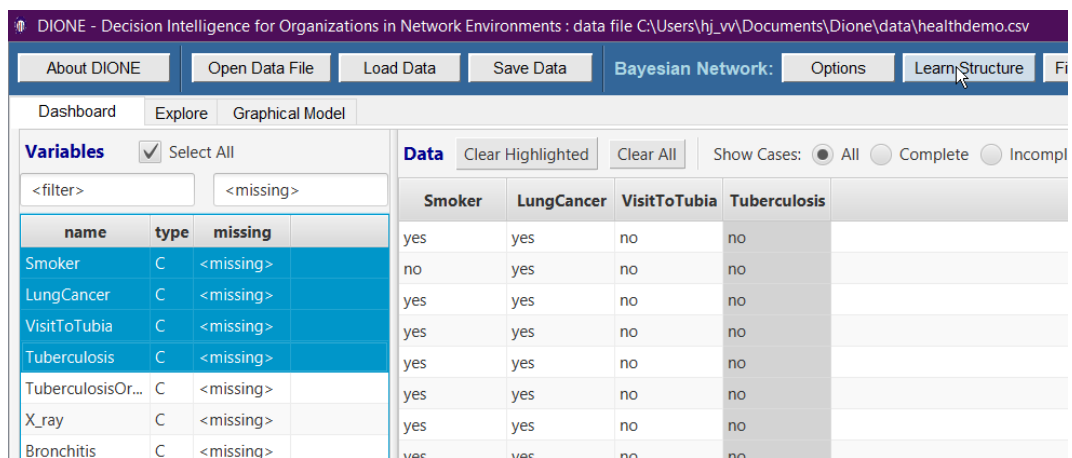
If undirected arrows are present in the learned network, you can give them a direction in the same way, pushing the **D** key to give an arrow a direction and possibly pushing it again to reverse the direction.

Fit Parameters

More information about causal relations between variables in the network can be gained by fitting parameters of the network to obtain conditional probability tables and regression coefficients, showing the (probabilities of) values of a node given values of its parent nodes. Parameters are estimated with a Maximum Likelihood algorithm.

When you are done editing network connections and the graph is completely directed, i.e. there are no undirected edges present, and the graph does not have cycles, you can calculate conditional probabilities, marginal probabilities and regression coefficients for numerical variables by pressing button **Fit Parameters** .

For clarity in the example shown here structure learning has been done with only four variables:

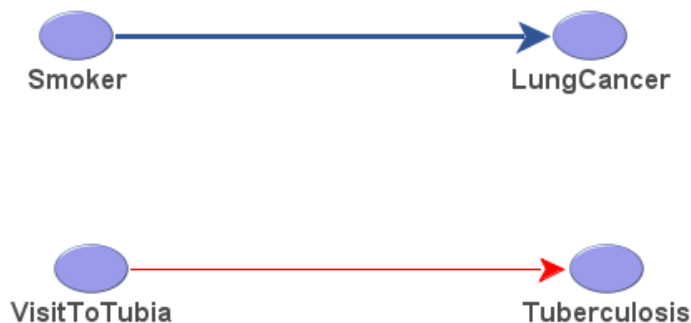


The screenshot shows the DIONE software interface. The top menu bar includes 'About DIONE', 'Open Data File', 'Load Data', 'Save Data', 'Bayesian Network:', 'Options', 'Learn Structure', and 'Fit Parameters'. The 'Learn Structure' button is highlighted. Below the menu bar, there are tabs for 'Dashboard', 'Explore', and 'Graphical Model'. The 'Variables' section on the left shows a list of variables with columns for 'name', 'type', and 'missing'. The 'Data' section on the right shows a table with columns for 'Smoker', 'LungCancer', 'VisitToTubia', and 'Tuberculosis'. The data table contains 10 rows of data.

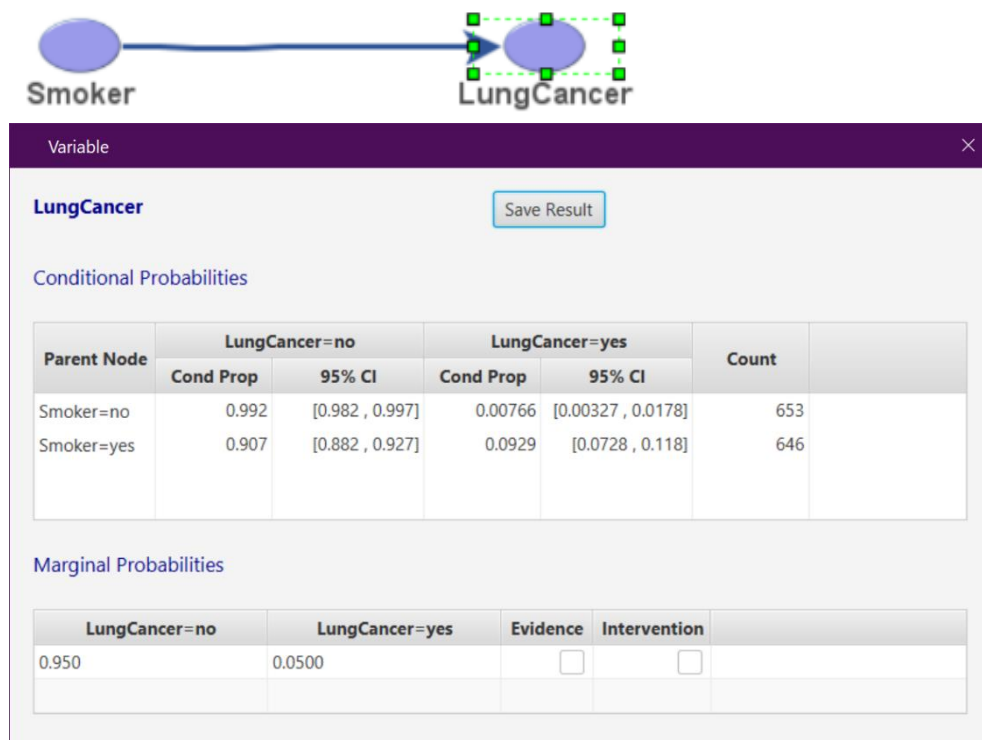
name	type	missing
Smoker	C	<missing>
LungCancer	C	<missing>
VisitToTubia	C	<missing>
Tuberculosis	C	<missing>
TuberculosisOr...	C	<missing>
X_ray	C	<missing>
Bronchitis	C	<missing>

Smoker	LungCancer	VisitToTubia	Tuberculosis
yes	yes	no	no
no	yes	no	no
yes	yes	no	no
yes	yes	no	no
yes	yes	no	no
yes	yes	no	no
yes	yes	no	no
yes	yes	no	no
yes	yes	no	no
yes	yes	no	no

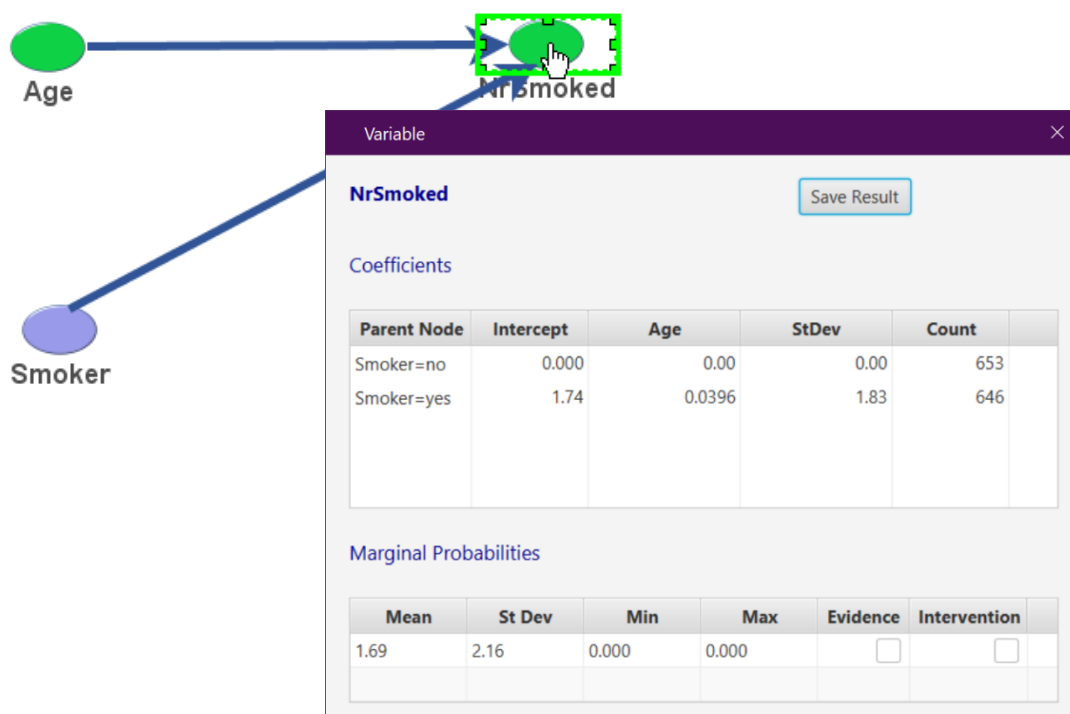
After some editing, we have this simple network:



When the parameter fitting algorithm has finished, right-click on any node of a categorical variable (shown in blue) to see its conditional probability table, showing conditional probabilities given the values of its parents, along with 95 % confidence intervals for these conditional probabilities. At the bottom of the dialog marginal probabilities of the node are shown:



For a node of a numerical variable (shown in green), coefficients of regression equations are displayed, along with the standard deviation of the residuals. In this example, variable **NrSmoked** depends on the two variables **Age** and **Smoker**. **Smoker** has two possible values, so there are regression equations reflecting the dependence of **NrSmoked** on **Age** for each of the values of **Smoker**:



Infer Probabilities

Now you can perform inference on the Bayesian network by setting evidence on one or more nodes, then pressing button **Infer Probabilities** to recompute marginal probabilities and see the effect of the evidence on the other nodes:

The screenshot shows a software interface for Bayesian network inference. The top menu bar includes buttons for 'Learn Structure', 'Fit Parameters', 'Infer Probabilities', 'Stop Algorithm', and 'Save'. The main window is divided into two panels: 'Smoker' and 'LungCancer'.

Smoker Panel:

Conditional Probabilities

Parent Node	Smoker=no		Smoker=yes		Count
	Cond Prop	95% CI	Cond Prop	95% CI	
env=e	0.503	[0.476, 0.530]	0.497	[0.470, 0.524]	1299

Marginal Probabilities

Smoker=no	Smoker=yes	Evidence	Intervent
0.000	1.000	<input checked="" type="checkbox"/>	

LungCancer Panel:

Conditional Probabilities

Parent Node	LungCancer=no		LungCancer=yes
	Cond Prop	95% CI	
Smoker=no	0.992	[0.982, 0.997]	0.0076
Smoker=yes	0.907	[0.882, 0.927]	0.092

Marginal Probabilities

LungCancer=no	LungCancer=yes	Ev
0.913	0.0917	

A red circle highlights the 'Smoker=yes' cell in the Smoker Marginal Probabilities table, and another red circle highlights the 'LungCancer=yes' cell in the LungCancer Marginal Probabilities table. An arrow points from the first circle to the second, indicating the causal relationship between the evidence and the updated probability.

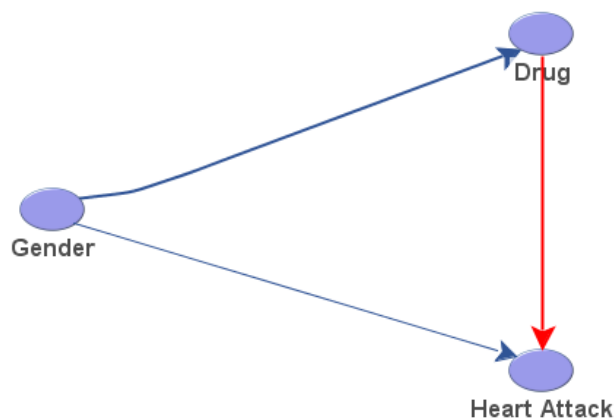
In this example the probability of lung cancer has increased from 5 % to over 9 % on the evidence that someone is a smoker.

We can also infer the effects of interventions, as illustrated by the following example related to the famous Simpson paradox. The Simpson paradox occurs in these fictitious data on gender, taking of a drug and risk of a heart attack (from Pearl & Mackenzie 2018):

	Control Group (No Drug)		Treatment Group (Took Drug)	
	Heart Attack	No Heart Attack	Heart Attack	No Heart Attack
Female	1	19	3	37
Male	12	28	8	12
Total	13	47	11	49

From these data it seems that the drug increases the risk of a heart attack for women, as $3/40$ (7.5%) > $1/20$ (5%), it also increases the risk for men, as $8/20$ (40%) > $12/40$ (30%), yet it decreases the risk for the population as a whole, as $11/60$ (18.33%) < $13/60$ (21.67%).

This is shown in **DIONE** by the data in file simpson.csv: [Learn Structure](#) and add an arrow to the learned network



After **Fit Parameters** right-click on the **Heart Attack** node to see its conditional probabilities:

Heart Attack					
Save Result					
Conditional Probabilities					
Parent Node	Heart Attack=no		Heart Attack=yes		Count
	Cond Prop	95% CI	Cond Prop	95% CI	
▼ Drug=no					
Gender=F	0.950	[0.764 , 0.991]	0.0500	[0.00888 , 0.236]	20
▼ Drug=no					
Gender=M	0.700	[0.546 , 0.819]	0.300	[0.181 , 0.454]	40
▼ Drug=yes					
Gender=F	0.925	[0.801 , 0.974]	0.0750	[0.0258 , 0.199]	40
▼ Drug=yes					
Gender=M	0.600	[0.387 , 0.781]	0.400	[0.219 , 0.613]	20

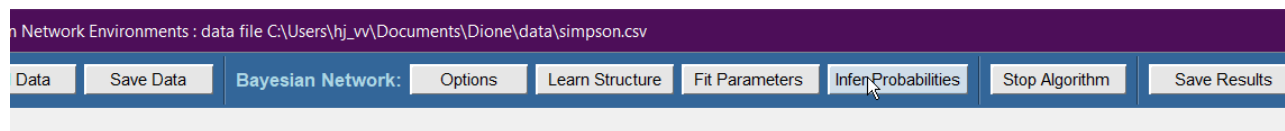
The conditional probabilities of getting a heart attack according to gender are the same as the percentages in the table. Yet, when comparing variables Drug and Heart Attack in the

Dashboard tab, we see these percentages for the population:

Variable	Drug			
	no		yes	
Heart Attack				
no	47	78.33%	49	81.67%
yes	13	21.67%	11	18.33%
Total	60	100.00%	60	100.00%

The paradox is resolved by realizing that **Gender** is a confounding variable that influences both the risk of a heart attack and the probability of taking the drug: women have less risk of a heart attack, but also take the drug more often than men. To correctly estimate the effect of the drug on the risk of a heart attack, we must adjust for gender and estimate the risk of a heart attack when taking the drug by averaging the percentages for men and women.

The paradox is illustrated in **DIONE** by inferring the probability of a heart attack given observational *evidence* of taking the drug, compared to the effect of an *intervention* to take the drug. Setting evidence that the drug has been taken and inferring probabilities gives the following results, with a probability of a heart attack of 18.3% when taking the drug and 21.7% when not taking the drug:



```

    graph TD
      Gender((Gender)) --> Drug((Drug))
      Gender --> HeartAttack((Heart Attack))
      Drug --> HeartAttack
  
```

Variable: Drug

Save Result

Conditional Probabilities

Parent Node	Drug=no		Drug=yes		Count
	Cond Prop	95% CI	Cond Prop	95% CI	
Gender=F	0.333	[0.227, 0.459]	0.667	[0.541, 0.773]	60
Gender=M	0.667	[0.541, 0.773]	0.333	[0.227, 0.459]	60

Marginal Probabilities

Drug=no	Drug=yes	Evidence	Intervention
0.000	1.000	<input checked="" type="checkbox"/>	<input type="checkbox"/>

Marginal Probabilities

Heart Attack=no	Heart Attack=yes	Evidence	Intervention
0.817	0.183	<input type="checkbox"/>	<input type="checkbox"/>

Marginal Probabilities

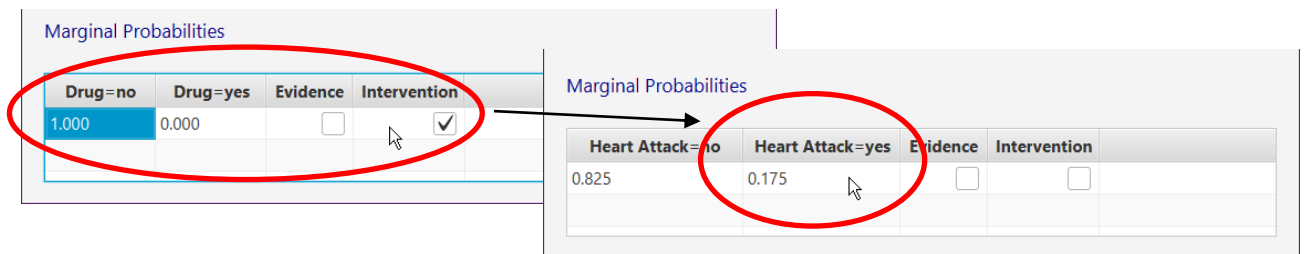
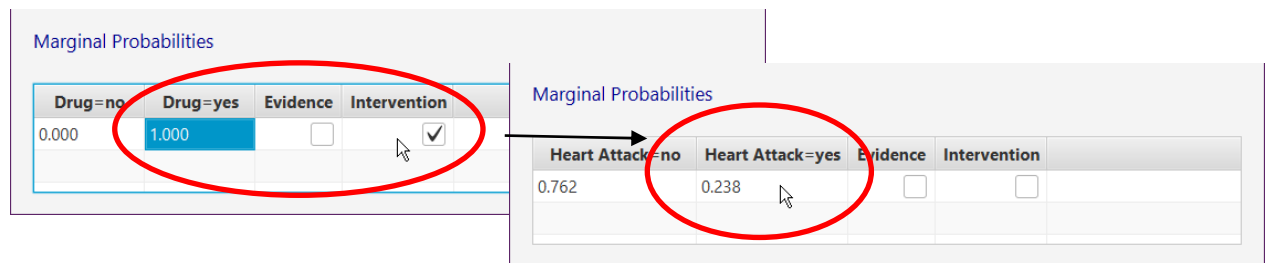
Drug=no	Drug=yes	Evidence	Intervention
1.000	0.000	<input checked="" type="checkbox"/>	<input type="checkbox"/>

Marginal Probabilities

Heart Attack=no	Heart Attack=yes	Evidence	Intervention
0.783	0.217	<input type="checkbox"/>	<input type="checkbox"/>

The evidence means we have only observed that the drug has been taken without doing anything, and the inference will include the effect of the confounding variable **Gender**, so the incorrect conclusion could be drawn that the drug is beneficial for the population.

When setting an *intervention* to take the drug, evidence is also set that the drug has been taken, but now the effect of confounding is eliminated by disregarding the arrow from **Gender** to **Drug** in the network. We are assuming the drug is now given to people, without considering gender. This gives the following inference results:



An intervention means we have given the drug to people regardless of gender, and the inference will eliminate the effect of the confounding variable **Gender**, so the correct conclusion can be drawn that the drug increases the risk of a heart attack for the population.

Copy and Save Results

You can keep your results by copying the network graph to another application, for example to insert it in a word processing document, or by saving it to a file. After fitting parameters, you can also save numerical results to a text file.

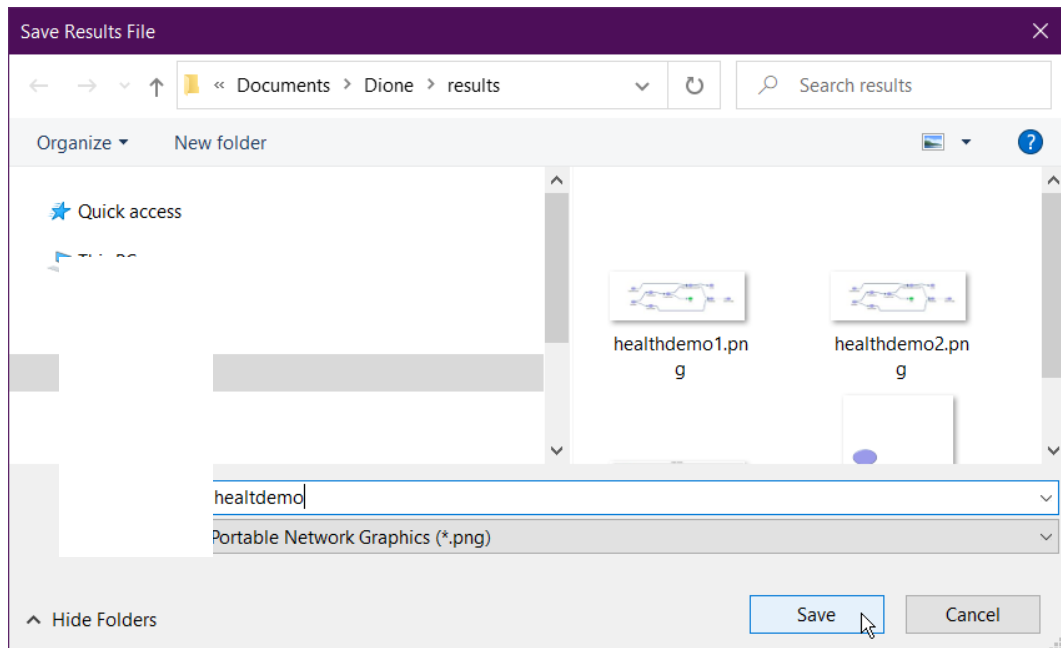
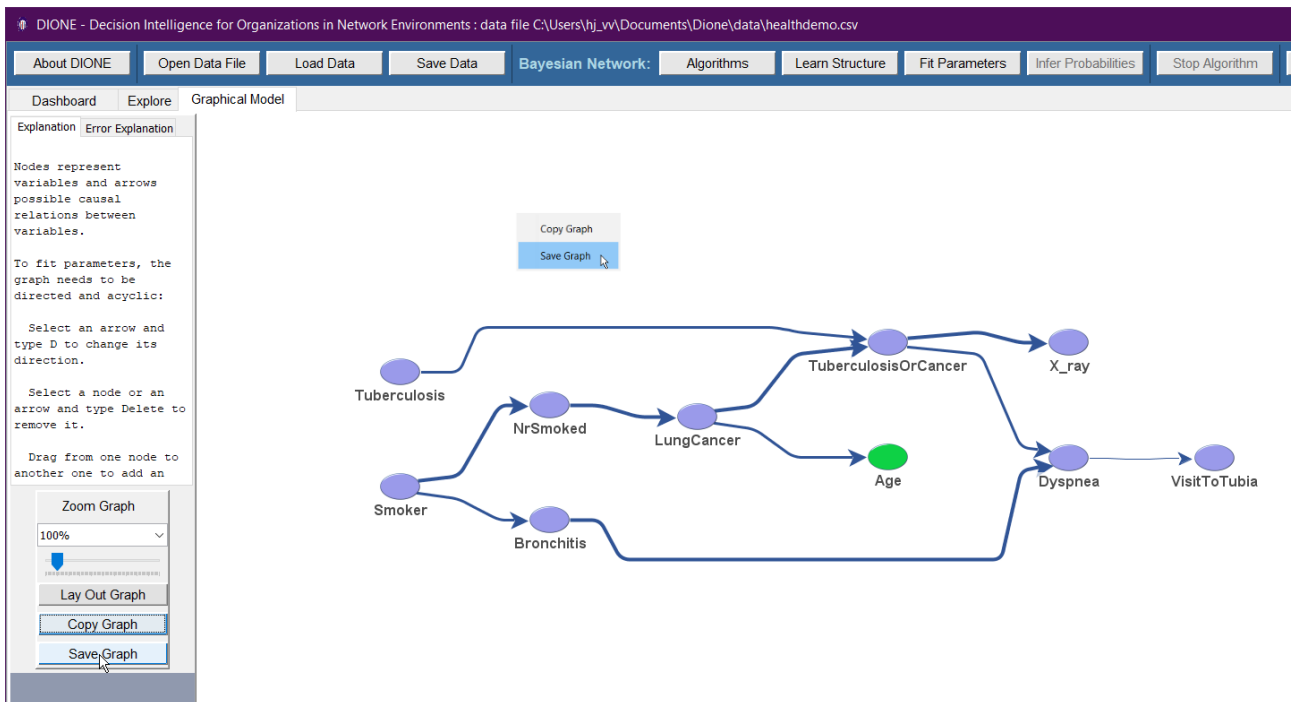
To copy the network graph, press button **Copy Graph** in the left-hand panel to put a picture of the chart on your computer's clipboard, or, if you prefer, you can right-click on the background of the graph and select **Copy Graph** from the pop-up menu:

The screenshot shows the DIONE software interface. The title bar reads "DIONE - Decision Intelligence for Organizations in Network Environments : data file C:\Users\hj_v\Documents\Dione\data\healthdemo.csv". The menu bar includes "About DIONE", "Open Data File", "Load Data", "Save Data", "Bayesian Network:", "Algorithms", "Learn Structure", "Fit Parameters", "Infer Probabilities", and "Stop Algorithm". The "Graphical Model" tab is active, showing a network graph with nodes: Tuberculosis, Smoker, NrSmoked, Bronchitis, LungCancer, Age, TuberculosisOrCancer, X_ray, Dyspnea, and VisitToTubia. A context menu is open over the graph with "Copy Graph" and "Save Graph" options. On the left, a panel contains instructions for graph manipulation and a "Copy Graph" button.

You can now paste the picture in a Word document, for example:

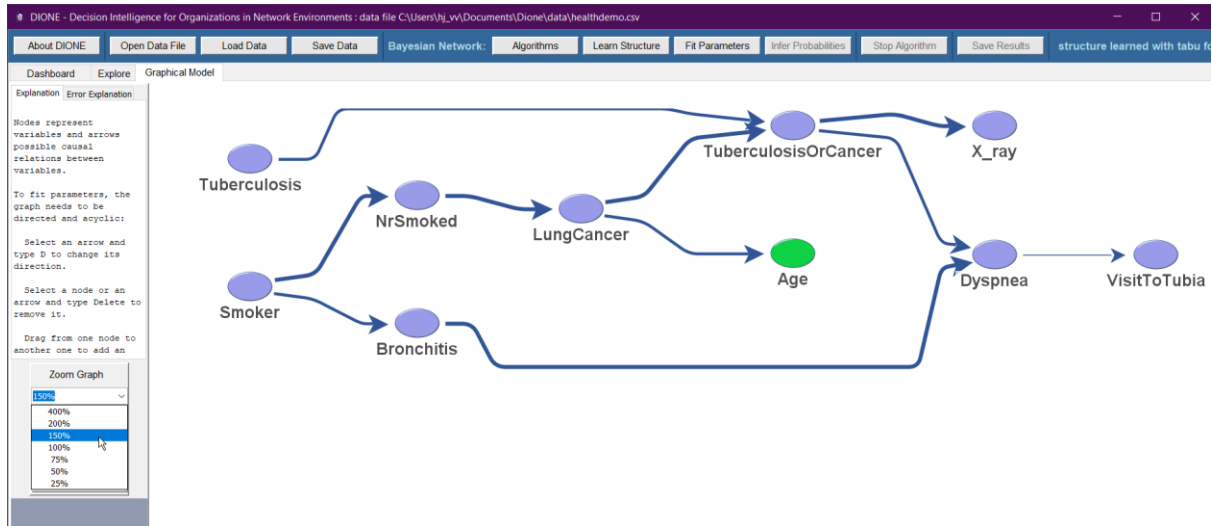
The screenshot shows a Microsoft Word document. The ribbon includes "Clipboard", "Font", "Paragraph", "Styles", "Editing", "Voice", "Sensitivity", and "Editor". The main text area contains the same Bayesian network graph as shown in the previous screenshot, which has been pasted from the DIONE software.

Press button **Save Graph** in the left-hand panel to save a network graph to a file, or right-click on the graph background and select **Save Graph** from the pop-up menu:



You now have a Portable Network Graphics (PNG) picture file that you can open in any image processing program or insert in a document.

With option **Zoom Graph** in the left-hand panel you can zoom in or out the network graph:



With option **Lay Out Graph** you can redraw the graph with a nice layout, if it has become messy after a lot of manual editing, for example.

Save Data

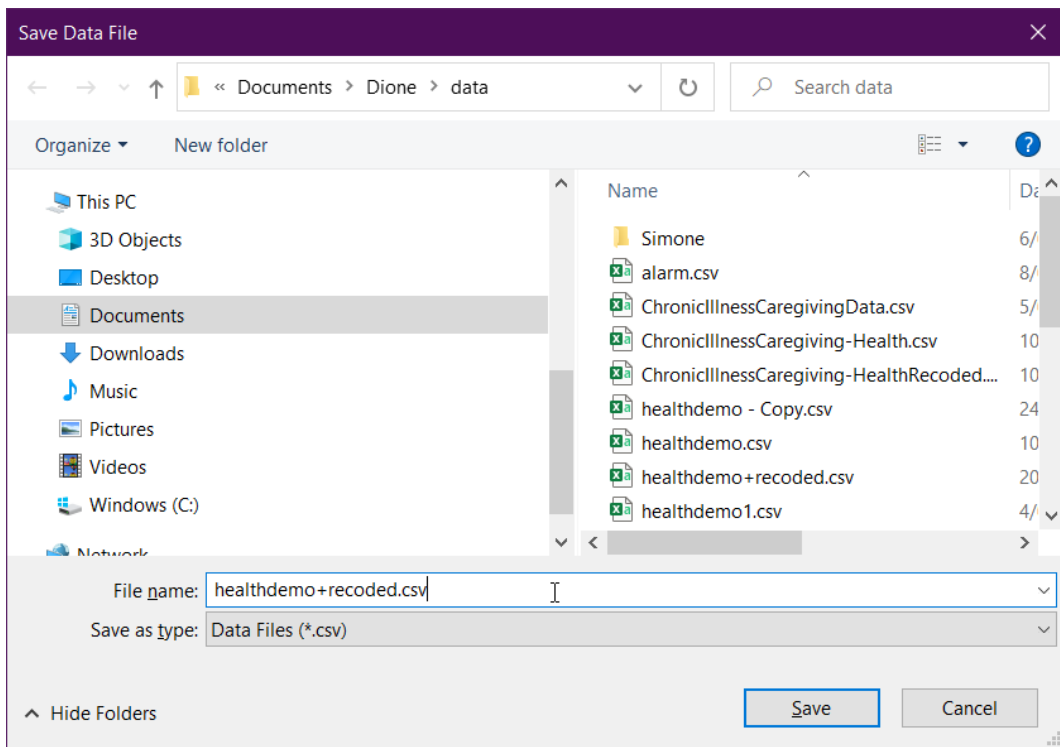
In the current version only data saving to CSV files is supported and in the saved CSV file column headers contain variable names, with values in the columns. The saved data file will have all data of variables shown in the **Variables** table, including any recoded data, for example the recoded **Age** variable here:

The screenshot displays the DIONE software interface. The main window shows a data table with 1299 cases for 11 variables. The variables listed are Age_2groups, Smoker, LungCancer, VisitToTubia, Tuberculosis, Tuberculosis OrCancer, X_ray, Bronchitis, and Dyspnea. The data table shows the following columns: Age_2groups, Smoker, LungCancer, VisitToTubia, Tuberculosis, Tuberculosis OrCancer, X_ray, Bronchitis, and Dyspnea. The data is organized into rows, with the first row showing '35-83' for Age_2groups, 'yes' for Smoker, 'yes' for LungCancer, 'no' for VisitToTubia, 'no' for Tuberculosis, 'yes' for Tuberculosis OrCancer, 'yes' for X_ray, 'yes' for Bronchitis, and 'yes' for Dyspnea. The interface also includes a 'Variables' table on the left and two histograms on the right. The top histogram is titled 'Variable: Age' and shows a distribution of values from 5 to 85. The bottom histogram is titled 'Age_2groups' and shows a distribution of values from 6-34 and 35-83. A summary table at the bottom right provides the following data:

Variable	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Age				
[6.0 - 13.7]	11	0.85%	11	0.85%
[13.7 - 21.4]	50	3.85%	61	4.70%
[21.4 - 29.1]	142	10.93%	203	15.63%
[29.1 - 36.8]	273	21.02%	476	36.65%
[36.8 - 44.5]	350	26.94%	826	63.59%
[44.5 - 52.2]	249	19.17%	1,075	82.76%

Note that the saved data will not include data for any variables you have removed from the **Variables** table. If radio button Complete or Incomplete has been selected, only complete or incomplete cases will be saved.

To save data to a CSV file, press button **Save Data** and in the **Save Data File** dialog enter a name for the data file you wish to create:



The saved data file now looks like this:

	A	B	C	D	E	F	G	H	I	J	K	L
1	Age_recoded1	Smoker	LungCancer	VisitToTubia	Tuberculosis	TuberculosisOrCancer	X-ray	Bronchitis	Dyspnea	Age	NrSmoked	
2	31-57	yes	yes	no	no	yes	yes	yes	yes	53	9	
3	57-83	no	yes	no	no	yes	yes	no	no	62	0	
4	57-83	yes	yes	no	no	yes	yes	no	yes	62	8	
5	57-83	yes	yes	no	no	yes	yes	yes	yes	74	10	
6	31-57	yes	yes	no	no	yes	yes	no	yes	47	6	
7	31-57	yes	yes	no	no	yes	yes	yes	no	57	4	
8	57-83	yes	yes	no	no	yes	yes	yes	yes	71	10	
9	57-83	yes	yes	no	no	yes	yes	yes	yes	61	6	
10	31-57	no	yes	no	no	yes	yes	no	yes	53	0	
11	31-57	yes	yes	no	no	yes	yes	no	yes	48	4	
12	57-83	yes	yes	no	no	yes	yes	yes	yes	72	9	
13	31-57	yes	yes	no	no	yes	yes	yes	yes	46	8	
14	57-83	yes	yes	no	no	yes	yes	yes	yes	61	7	
15	57-83	yes	yes	no	yes	yes	yes	no	yes	62	9	
16	31-57	no	yes	no	no	yes	yes	no	yes	41	0	
17	31-57	yes	yes	no	no	yes	yes	no	yes	35	9	
18	31-57	no	yes	no	no	yes	yes	no	no	40	0	
19	31-57	yes	yes	no	no	yes	yes	yes	yes	56	5	
20	31-57	yes	yes	no	no	yes	yes	yes	yes	37	6	
21	57-83	yes	yes	no	no	yes	yes	no	yes	62	7	
22	57-83	yes	yes	no	no	yes	yes	yes	yes	60	9	
23	57-83	yes	yes	no	no	yes	yes	no	yes	58	5	
24	31-57	yes	yes	no	no	yes	yes	yes	yes	41	6	

Big Data – Performance

DIONE uses efficient R algorithms to load, process and save data, which is quite fast for datasets of up to some 1 million rows of data (also known as cases or records), even on an average laptop PC.

However, when memory and processing power are limited, these tasks become more time-consuming. Some typical times are given here:

computer	processor Intel i7, memory 4 GB
number of variables	31
number of cases	10 000 000
loading data	2 minutes
checking complete cases	3 minutes
number of complete cases	1 500 000
learning network structure	17 minutes
fitting parameters	6 minutes

References

Judea Pearl & Dana Mackenzie 2018. *The Book of Why – The New Science of Cause and Effect*. Allen Lane, Great Britain.