

KE5107: Data Mining Methodology and Methods

# Workshop: Data Preparation & Transformation

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# What we know about the dataset

- We are working on “weather” dataset from Rattle Library
- From our earlier workshop, we’ve discovered
  - There are missing values in the data
  - Some variables are skewed (e.g. Rainfall, WindSpeed9am)
  - There are variables with duplicated information (e.g. Temp3pm and MaxTemp, Pressure9am and Pressure3pm)
  - Some variables have more different distribution in records with “RainTomorrow =Yes” and records with “RainTomorrow =No”
  - “RISK\_MM” is actually describing the amount of rain TOMORROW!

# Missing Values in R

- In R, missing values are represented by the symbol **NA**
- Impossible values – NaN (not a number, e.g. dividing by 0)
- Testing of missing values – *is.na()* returns TRUE or FALSE
- Some functions have an option of ignoring missing values, like  
*mean(mpg, na.rm=TRUE)*
- To check which cases are complete, use function *complete.cases()*, returning a logical vector
  - Very useful for finding rows with missing values  
*weather[!complete.cases(weather), ]*

# Missing Values

- The situation of missing data in our dataset: most of the records are fine, and those with missing values are only missing 1 to 2 values.

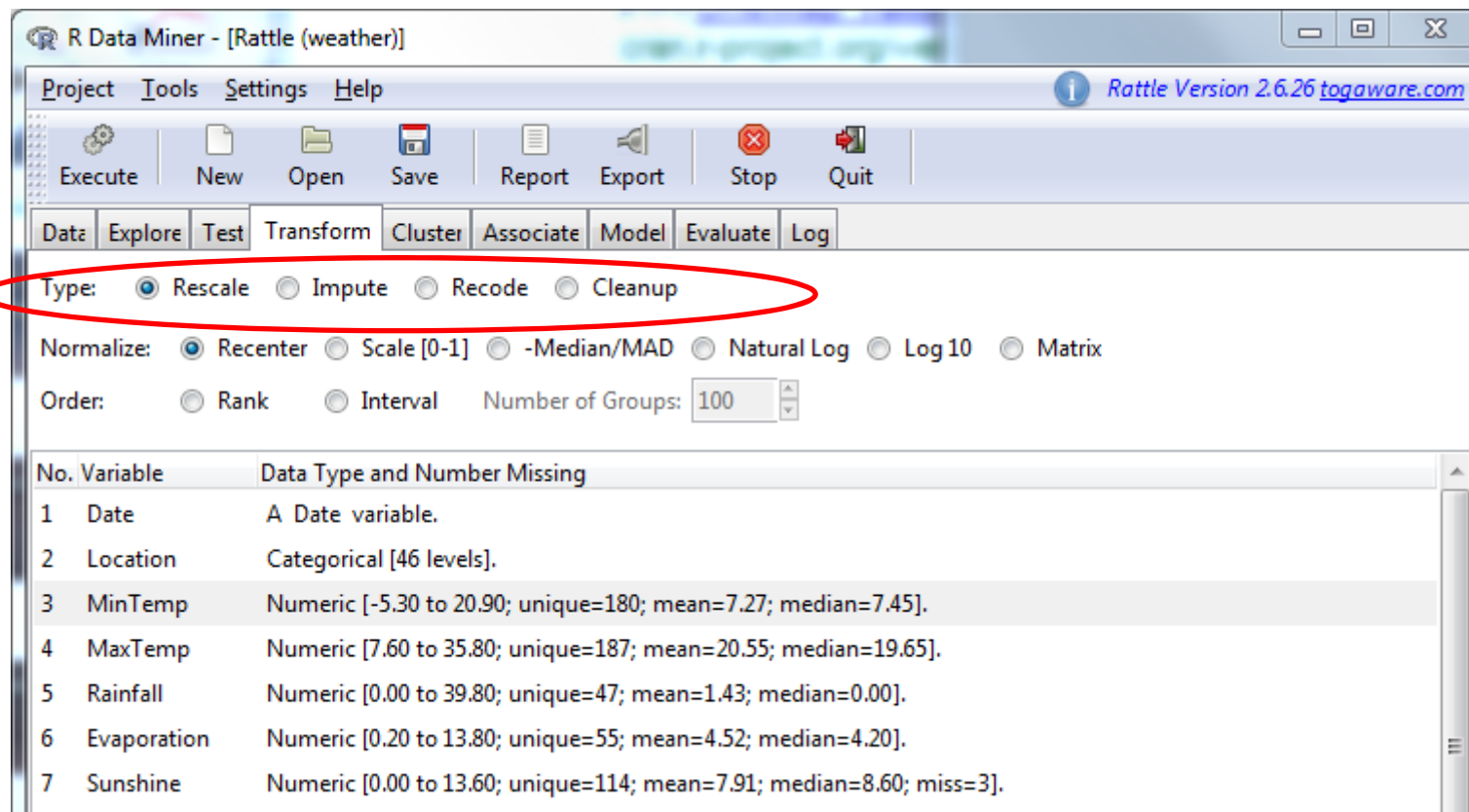
[illegible]

# Missing Values

- One variable have more missing values than others (WindDir9am)
- If this variable is very useful for prediction, we can try imputation. Otherwise, it can be ignored.

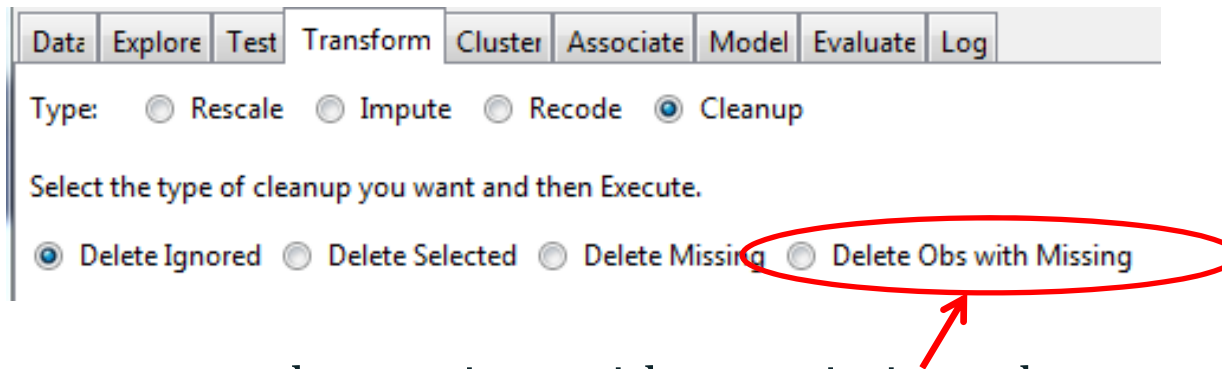
	RainToday	RainTomorrow	WindDir3pm	WindGustSpeed	Sunshine	WindGustDir
328	1	1	1	1	1	1
3	1	1	1	1	0	1
1	1	1	1	1	1	0
24	1	1	1	1	1	1
1	1	1	0	1	1	1
2	1	1	1	0	1	0
7	1	1	1	1	1	1
	0	0	1	2	3	3
<hr/>						
	WindSpeed9am	WindDir9am				
328	1	1	0			
3	1	1	1			
1	1	1	1			
24	1	0	1			
1	1	1	1			
2	1	1	2			
7	0	0	2			
	7	31	47			

# Rattle Transform Tab



# To Cleanup Missing Values

- To delete columns and observations
  - Delete Ignored: remove any variables set as Ignore
  - Delete Selected: remove any selected variables
  - Delete Missing: remove any variables with missing values
  - Delete Obs with Missing: remove rows with missing values



- If we want to remove observations with any missing values
- Code to remove rows with missing values

*new\_weather <- na.omit(weather)*

Should we do that?

# Imputation

- Dealing with missing values
  - Zero/Missing: replacing missing value with 0 (for numerical), or Missing (for categorical)
  - Mean/Median/Mode: use “central” value of the variable to reduce impact on the distribution (*mean* for generally normally distributed data, *median* for skewed data, *mode* for categorical)
  - Constant: to use your own default value

Type: ☐ Rescale ☒ Impute ☐ Recode ☐ Cleanup

Select the required imputation method and the variables to apply this to, then click Execute:

☒ Zero/Missing ☐ Mean ☐ Median ☐ Mode ☐ Constant:

No.	Variable	Data Type and Number Missing
6	Evaporation	Numeric [0.20 to 13.80; unique=55; mean=4.52; median=4.20].
7	Sunshine	Numeric [0.00 to 13.60; unique=114; mean=7.91; median=8.60; miss=3].

- Which method is better here?



# Impute Sunshine

- Try Zero/Missing, Mean, Median imputation on Sunshine, which has 3 missing values
- Original Sunshine

```
7 Sunshine      Numeric [0.00 to 13.60; unique=114; mean=7.91; median=8.60; miss=3;
```

- After imputation. Which one is better?

```
31 IZR_Sunshine  Numeric [0.00 to 13.60; unique=114; mean=7.84; median=8.60].
32 IMN_Sunshine  Numeric [0.00 to 13.60; unique=115; mean=7.91; median=8.60].
33 IMD_Sunshine  Numeric [0.00 to 13.60; unique=114; mean=7.92; median=8.60].
```

- Notice that after transformation, the original variable is automatically set to “Ignore”
- **Exercise:** Handle some other variables with missing values

# View the Code

```
# Impute Sunshine.

crs$dataset[["IMD_Sunshine"]] <- crs$dataset[["Sunshine"]]

# Change all NAs to the median (not advisable).

if (building)
{
  crs$dataset[["IMD_Sunshine"]][is.na(crs$dataset[["Sunshine"]])] <- median(crs$dataset[["Sunshine"]], na.rm=TRUE)
}

# When scoring, transform using the training data parameters:

if (scoring)
{
  crs$dataset[["IMD_Sunshine"]][is.na(crs$dataset[["Sunshine"]])] <- 8.6
}

# Impute Sunshine.

crs$dataset[["IZR_Sunshine"]] <- crs$dataset[["Sunshine"]]

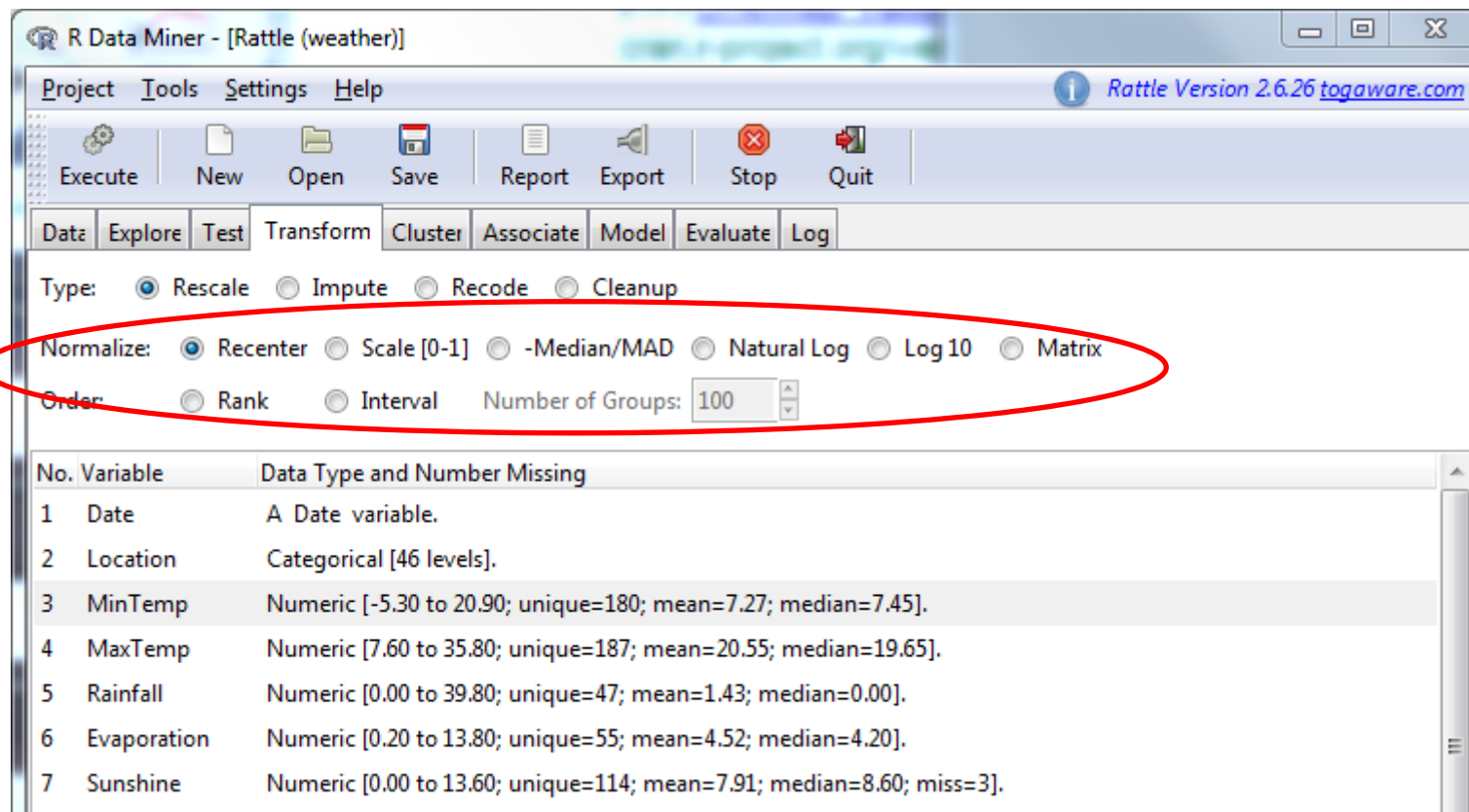
# Change all NAs to 0.

if (building)
{
  crs$dataset[["IZR_Sunshine"]][is.na(crs$dataset[["Sunshine"]])] <- 0
}

# When scoring, transform using the training data parameters:

if (scoring)
{
  crs$dataset[["IZR_Sunshine"]][is.na(crs$dataset[["Sunshine"]])] <- 0
}
```

# Rescaling



# Rescaling

- Normalization
  - Recenter: Z score, the mean of scaled data is 0
  - Scale [0-1]: normalized to be in the range from 0 to 1
  - Median/MAD: robust rescaling around 0 using the median
  - Natural Log
  - Log 10
  - Matrix: transform multiple variables with one divisor
- Order
  - Rank: convert numbers into a rank ordering
  - Interval: rescale a variable according to some group that the observation belongs to
- Let's try a few methods on one variable *Temp3pm* for comparison (select one, click "Execute". Then repeat with another method.)

# Rescaled Variables

- Rescaled variables are inserted into the table as new columns, with prefix indicating the kind of transformation

Original	20	Temp9am	Numeric [0.10 to 24.70; unique=178; mean=12.36; median=12.55].
	21	Temp3pm	Numeric [5.10 to 34.50; unique=200; mean=19.23; median=18.55; ignored].
	22	RainToday	Categorical [2 levels].
	23	RISK_MM	Numeric [0.00 to 39.80; unique=47; mean=1.43; median=0.00].
	24	RainTomorrow	Categorical [2 levels].
Transformed	25	RRC_Temp3pm	Numeric [-2.13 to 2.30; unique=200; mean=0.00; median=-0.10]. No code export.
	26	R01_Temp3pm	Numeric [0.00 to 1.00; unique=200; mean=0.48; median=0.46]. No code export.
	27	RMD_Temp3pm	Numeric [-1.87 to 2.22; unique=200; mean=0.09; median=0.00]. No code export.
	28	RLG_Temp3pm	Numeric [1.63 to 3.54; unique=200; mean=2.89; median=2.92]. No code export.
	29	R10_Temp3pm	Numeric [0.71 to 1.54; unique=200; mean=1.26; median=1.27]. No code export.
	30	RRK_Temp3pm	Numeric [1.00 to 366.00; unique=200; mean=183.50; median=183.75]. No code export.

# Check Distribution

- At *Explore* Tab, select “Distributions” Type, and check the original Temp3pm variable, and its scaled versions. Change “Plots per Page” to 6. Click “Execute”

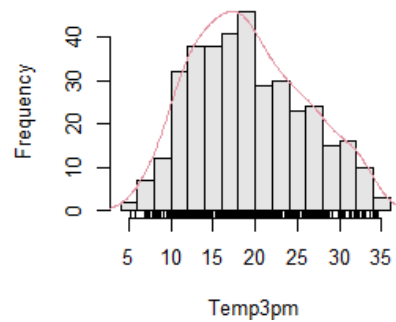
The screenshot shows the Data Explorer interface with the following settings:

- Tab:** Explore
- Type:** Distributions (selected)
- Numeric:** Clear
- Plots per Page:** 6 (circled in red)
- Annotate:** (unchecked)
- Benford Bars:** (unchecked)
- Benford Digit:** 1
- abs:** (selected)
- +ve:** (unchecked)
- ve:** (unchecked)

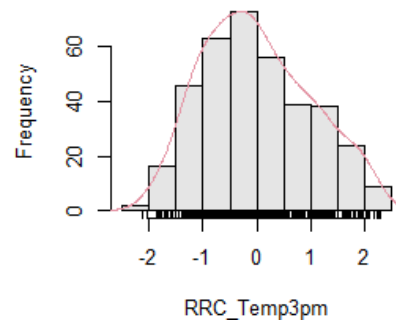
No.	Variable	Box Plot	Histogram	Cumulative	Benford	Min; Median/Mean; Max
19	Cloud3pm	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	0.00; 4.00/4.02; 8.00
20	Temp9am	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	0.10; 12.55/12.36; 24.70
21	Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	5.10; 18.55/19.23; 34.50
23	RISK_MM	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	0.00; 0.00/1.43; 39.80
25	RRC_Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	-2.13; -0.10/0.00; 2.30
26	R01_Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	0.00; 0.46/0.48; 1.00
27	RMD_Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	-1.87; 0.00/0.09; 2.22
28	RLG_Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	1.63; 2.92/2.89; 3.54
29	R10_Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	0.71; 1.27/1.26; 1.54
30	RRK_Temp3pm	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	1.00; 183.75/183.50; 366.00

# Distribution of Rescaled Variables

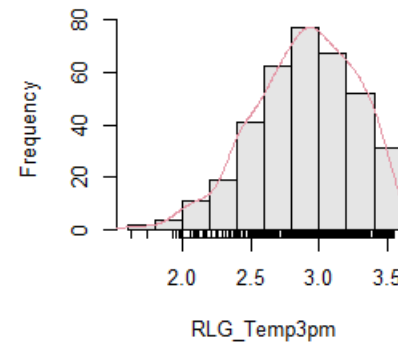
Distribution of Temp3pm



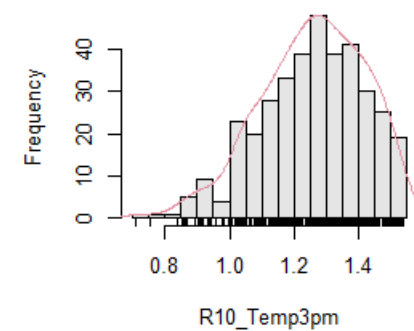
Distribution of RRC\_Temp3pm



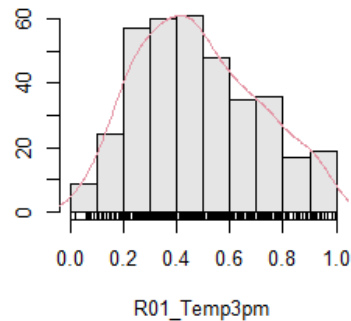
Distribution of RLG\_Temp3pm



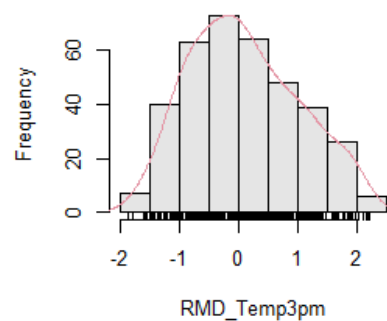
Distribution of R10\_Temp3pm



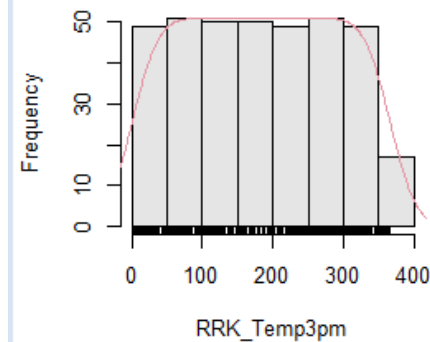
Distribution of R01\_Temp3pm



Distribution of RMD\_Temp3pm



Distribution of RRK\_Temp3pm



# Rescaling Exercise

- Rescale the two variables that were found skewed (Rainfall, WindSpeed9am)

Sidetrack (you can do this after class)

- Remember when we did Principle Component Analysis on mtcars dataset with method Eigen, the biplot doesn't look so right with original variables?
- Let's try rescaling all the variables to the same range [0-1]
- Do the PCA with Eigen again.
- Any change?

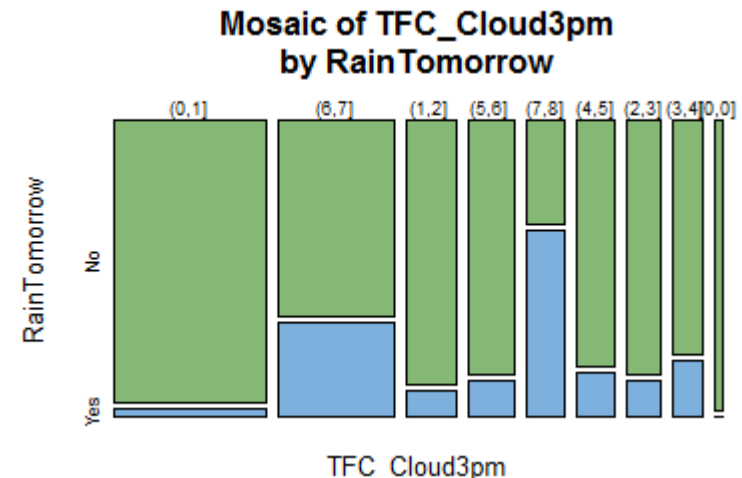
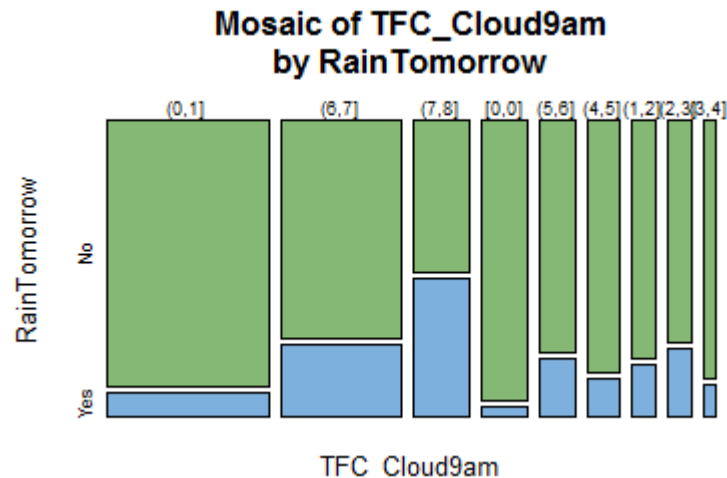


# Recoding

- Binning
  - Transforming a continuous numeric variable into categorical values based on the numeric values, e.g. from Age to Age Groups
  - Can be useful in simplifying models, or for visualization
- Indicator Variables
  - Transform a categorical variable into a set of indicator(1/0) variables
  - Some model builders in Rattle (like Linear) do this automatically
- Join Categories
  - Stratify the dataset based on multiple categorical variables, e.g. from RainToday(yes/no) and RainTomorrow (yes/no), generate a new variable (yes\_no/yes\_yes/no\_yes/no\_no)
- Type conversion: As Categorical, As Numeric

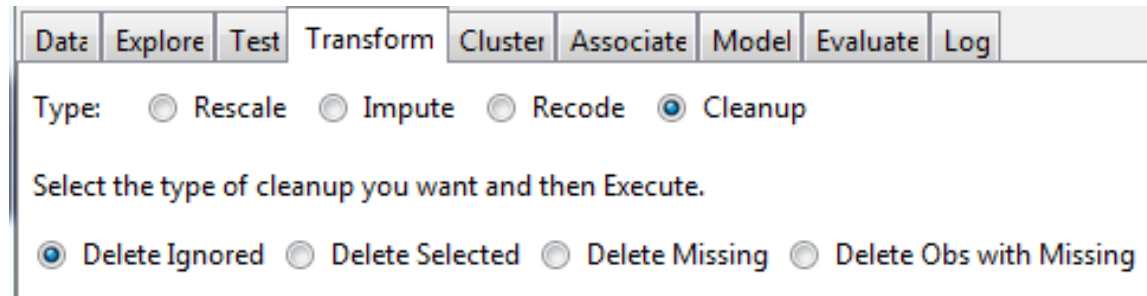
# Recoding

- Remember “Cloud9am” and “Cloud3pm” with <10 unique values? Would it be better to treat them as categorical variables?
- Let’s convert them using “As Categorical”
- Plot the converted variables. Any discovery? Should we keep the change?



# Cleanup

- To delete columns and observations
  - Delete Ignored: remove any variables set as Ignore
  - Delete Selected: remove any selected variables
  - Delete Missing: remove any variables with missing values
  - Delete Obs with Missing: remove rows with missing values



The screenshot shows the 'Transform' menu in JupyterLab. The 'Cleanup' option is selected under the 'Type:' section. Below it, the instruction 'Select the type of cleanup you want and then Execute.' is displayed. Four options are listed: 'Delete Ignored' (selected), 'Delete Selected', 'Delete Missing', and 'Delete Obs with Missing'.

Data	Explore	Test	Transform	Cluster	Associate	Model	Evaluate	Log
------	---------	------	-----------	---------	-----------	-------	----------	-----

Type: ☐ Rescale ☐ Impute ☐ Recode ☒ Cleanup

Select the type of cleanup you want and then Execute.

☒ Delete Ignored ☐ Delete Selected ☐ Delete Missing ☐ Delete Obs with Missing

# Cleaning up

- Let's clean up the dataset by removing unwanted variables
- The code of removing a variable is straight forward

```
# CLEANUP the Dataset

# Remove specific variables from the dataset.

crs$dataset$R01_Temp3pm <- NULL
crs$dataset$RMD_Temp3pm <- NULL
crs$dataset$RLG_Temp3pm <- NULL
crs$dataset$R10_Temp3pm <- NULL
crs$dataset$RRK_Temp3pm <- NULL
crs$dataset$IMN_Sunshine <- NULL
crs$dataset$IMD_Sunshine <- NULL
```

- Removing rows with missing values

*new\_weather <- na.omit(weather)*

# Exporting Transformed Data

- Then click “Export” button, and save the transformed dataset as “weather\_transformed.csv”

