B.Sc in Computing

# Enterprise Database Technologies CA 1

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## Section 1 - Data Understanding and Data Exploration

### Data pre-processing

First operation carried out was getting the number of null or empty string values per column (appendix 1.a).

We can see that only very few values are empty (single digit); and some columns have no value missing which indicates that our data is of good quality in terms of completeness.

The next step was to replace null numeric values with the median of the respective columns (appendix 1.b).

Then I created a function to get the mode by gender of a given column and replaced missing values in categorical columns by their respective modes (appendix 1.c).

The mode of PHONE\_PLAN is International for both Males and Females, there are also more Males churners than Females churners (plotting the influence of gender could be interesting).

### Discretizing income

One should be careful with the inclusion / exclusion of lower and upper ranges, the Low-Income category as an example end before 38,000 (37,999 is the last value), this is taken in account in the code.

### Finding information

For 3.c (appendix 3.c), the get\_mode function (created earlier), was used along with the summary function.

See appendix 3c, 3.d, 3.e, 3.f, 3.g for this question

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Predictor | A | B | C | D | E | F | G |
| AREA\_CODE | Nominal | 0 | **Mode**: 10040 | X | X | X | X |
| CUST\_MOS | Numeric | 3/2071 | **Min**: 1,  **Median**: 11,  **Mean**: 16.05,  **Max**:  50 | Most customers seem to stay during 5 to 15 months | It seems that in the first months, the customer has more chances to Churn, Around 10 months the customer will churn as well (end of one year contract?) | Skewness: 1.131244  Positively skewed (skewed to the right) | One outlier found in the box plot |
| LONGDIST\_FLAG | Nominal | 0 | **Mode**: 1 | X | X | X | X |
| CALLWAITING\_FLAG | Nominal | 0 | **Mode**: 0 | X | X | X | X |
| NUM\_LINES | Numeric | 0 | **Min**: 1,  **Median**: 1,  **Mean**: 1.391,  **Max**:  3 | Most users seem to have 1 number only and only very few have 3 numbers | The number of lines do not seem to bring much insight | Skewness: 2.057503  Strongly positively skewed (skewed to the right) | X |
| VOICEMAIL\_FLAG | Nominal | 0 | **Mode**: 1 | X | X | X | X |
| MOBILE\_PLAN | Nominal | 0 | **Mode**: 0 | X | X | X | X |
| CONVERGENT\_BILLING | Nominal | 0 | **Mode**: No | X | X | X | X |
| GENDER | Nominal | 0 | **Mode**:  M | X | Does not bring insight | X | X |
| INCOME | Ordinal | 0 | **Mode**:  Medium Income | Most users have medium income, twice as many users have high income compared to low income users | Users with low income or high income tend not to churn while medium incomes tend to churn more | X | X |
| PHONE\_PLAN | Ordinal | 4/2071 | Mode: **International** | Only few users choose the Euro-zone, most of the users opt for the International and National plans | Users having the Euro-Zone or the International phone plan tend to churn while users with a National or Promo\_plan tend to churn less | X | X |
| EDUCATION | Nominal | 8/2071 | Mode: **Post Primary** | Post-Primary is the dominant group, the number of High school and Primary school are very low | Primary are churners, Masters tend to churn, PhD tend not to churn | X | X |
| TOT\_MINUTES\_USAGE | Numeric | 4/2071 | **Min**: 0,  **Median**: 264,  **Mean**: 2036,  **Max**:  36237 | Clear majority of users use less than 2500 mins | Do not seem to bring insight | Skewness: 1.088757  Positively skewed (skewed to the right) | Graphically, from the boxplot we can see that the data contains a lot of outliers that will need to be cleaned out |

### Finding outliers mathematically

I chose TOT\_MINUTES\_USAGE since its box graph seems to indicate a lot of outliers.

I found 176 outliers using the IQR method while the Z-standardisation method found 69 outliers (appendix 4).

### Skewness in TOT\_MINUTES\_USAGE

My approach was, to first get the skewness value of TOT\_MINUTES\_USAGE before transformation: 1.088757, (appendix 5.), this positive skewness indicates that the data is skewed on the right (graphically we can see a long right tail). Most of the records will be on the left of the graph.

Z-score standardisation obtained the same skewness so no value was added, my observation is that Z-score uses mean and standard deviation which both are influenced by outliers (which are very present in TOT\_MINUTES\_USAGE). (appendix 5.a)

Natural log reduced skewness and made it a left-skewness (as opposed to the previous right skewness), it added value (appendix 5.b): -0.7042918

Square root increased the skewness, so it is not appropriate to use it with this data (appendix 5.c): 1.288432

### Relationship between variables and response

**a.**

To study the relationships, I used the same graphs plotted in appendix 3.e.

My approach was to plot histograms for each variable, colour encoded by the response variable.

Histograms where there are no disproportions between churners and non-churners on at least one of the values or range, might not be of any value for the prediction.

The question mentioned using only numeric variables, but, exploring the data showed more interesting results for overlaid graphs in some ordinal / nominal variables (included in the summary).

#### Variables that seem to influence churning (from this graphical method):

Income, where from the graph we can infer that Low and High Incomes are more frequent churners than Medium Incomes.

Phone plan, where we see that Euro-zone users are almost only churners, International users also have big churning rates while National and Promo-plan have low churning rates.

Education, where Primary have big churning rates and disproportions can be observed in all other categories besides Post Primary which seems to be balanced (might not help inferring rules).

Area codes where there are clear disproportions on each area.

#### Variables that seem to have no influence on churning (from this graphical method):

Number of lines and Gender seem to be both almost perfectly balanced, so they might be irrelevant to infer rules.

#### Variables for which the graph is not explicit:

Customer loyalty and Total minutes usage seem to show balance on some values while some other values show disproportions.

**b.**

I would expect Income or/and Area code to show up in the classification models as they seem to influence churning rate.

### 7. Correlated variables

**a.**

The sum of MINUTES\_CURR\_MONTH, MINUTES\_PREV\_MONTH, MINUTES\_3MONTHS\_AGO correlate with TOT\_MINUTES\_USAGE, the other variables are not correlated (appendix 7)

## Section 2 – Data Mining