How to do Effective and Sucessful Bank Telemarketing

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Author note

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Abstract :

In this project objective is to improve given Portuguese bank's tele marketing campaign efficiency by identifying socio economic attributes of Customers as the driving factor for term deposit product selection. Cross Industry Data Standard Process for data mining(CRISP DM) framework has been used in this project. With this approach Business case understanding was the first step, followed by data exploration, data preparation, modeling, evaluation and recommendation from final model. In given data set 16 variables related to Customers socio economic conditions have been analyzed for around 41188 Customer records. Three different models have been used in this project- Logistics Regression, Classification tree, RandomForest for classification of binary variable campaign response. Several criteria have been used for evaluation of those three models, some of the key indicators are model accuracy, (AUC), F1 score etc. Based on the model comparison data RandomForest has been found as the most efficient model with AUC score of around 92%for the given case scenario. Among predictor variables it is found call "duration" variable is the most important predictor with longer duration calls resulting in more productive discussion and success of the campaign. This was followed by variables euribor3m and nr.employed.

With given data set % of response records are disproportionate compared to the population, around 10% success out of data set. This is real life scenario but creates challenges for the model. To take care of that Area under curve (AUC)metrics has been used for final model selection rather than the accuracy number.

Introduction :

describe the background and motivation of your problem–

After looking at various options, we settled for this project for our final since it met all the requirements.

"Regression analysis is one of the most commonly used statistical techniques in social

and behavioral sciences as well as in physical sciences. Its main objective is to explore the relationship between a dependent variable and one or more independent variables (which are also called predictor or explanatory variables)." This is the definition provided by www.unesco.org for Regression Analysis

The most successful direct marketing is to predict the customers that have a higher probability to do business. Data exploration technique, is crucial to understand customer behavior. Many banks and services are moving to adopt the predictive technique based on the data mining to predict the customer profile before targeting them. The prediction or classification is the most important task in the data exploration and model building that is usually applied to classify the group of data. In classification, the outcome is a categorical variable and several combinations of input variable are used to build a model and the model that gives a better prediction with the best accuracy is chosen to target the prospective customers.

The data set contains approximately 41188 obs. of 21 variables.

This dataset is based on "Bank Marketing" UCI dataset (please check the description at: http://archive.ics.uci.edu/ml/datasets/Bank+Marketing). The data is enriched by the addition of five new social and economic features/attributes (national wide indicators from a ~10M population country), published by the Banco de Portugal and publicly available at: https://www.bportugal.pt/estatisticasweb.

The binary classification goal is to predict if the client will subscribe a bank term deposit (variable y).

This dependent variable tells whether the client will subscribe a bank term deposit or not. This is a binary variable and as such we will be using a Logistic Regression Model.

Literature Review :

There have been a few papers that have discussed this requirement. A common thread acro

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Data Imbalance (as discussed in 1) was another factor that was considered in one of the

Duration was one of the variables highlighted in almost all papers. Some of the papers r
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References:

(1) • Who Will Subscribe A Term Deposit? Jiong Chen (jc4133), Yucen Han (yh2645), Zhao Hu (zh2210), Yicheng Lu (yl3071), Mengni Sun (ms4783)

(2) Predictive Modeling to Improve Success Rate of Bank Direct Marketing Campaign - Vaidehi R

(3) A Data Mining Approach for Bank Telemarketing Using the rminer Package and R Tool - Sérgio Moro, Paulo Cortez , Raul M. S. Laureano

Methodology :

In this project we will be using CRISP DM methodology.

Business Understanding

Data Exploration

The data is available on website for UC Irvine Machine Learning Repository. There are two different data sets available. The "bank" data has 45,211 records with 16 attributes and 1 response variable. The "bank-additional" data has 41,188 records with additional attributes added to "bank" data, it has 20 attributes and 1 response variable. We chose to use the data with additional attributes.

The data consists of four groups of information. - Client's personal information - Client's bank information - Bank's telemarketing campaign information - Social and economic information

The main problem with the dataset is that it consists of many missing values which are labeled "Unknown". The missing data consists of 26% of the data. We decided to retain the

missing data to help with our regression modeling. The other problem with the data is that only 12% of the data shows the response variable to be "y".

We looked at each variable and the unique values contained in each variable and what they represented. We can divide the variables in the following three categories:

1 - Binary values of "yes" and "no" wit null values given as "unknown". 2 - Categorical values with "unknown" as missing values. The categorical variable require dummy variables to be created for each unique value. We included "unknown" as one of the dummy variable. 3 - numeric values with "999" as indication of null value. We created a variable to indicate if the data was missing or present.

Also following two areas have been explored in the training data set. -Missing values and Unique Values -Variables relationship to y

We notice that the variables are numerical, categorical and binary. The response variable y is binary.

Based on the original dataset, our predictor input has 21 variables. And our response variable is 1 variable called y.

Binomial Logistic regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Like all regression analyses, the logistic regression is a predictive analysis. Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more metric (interval or ratio scale) independent variables.

Table 1

Variable Analysis

Variable	Data.Type	Analysis
age	Numeric	No significant trend with responses variable, better response with age grp<
job	Catagorical	12 levels, proportion of responses from admin and blue collar job profiles ar
marital	Catagorical	4 levels, % response from marital status from single is greater compare to o

Variable	Data.Type	Analysis
education	Catagorical	8 levels, responses from education with university degree are higher
default	Binary	3 levels, response is from no default group is dominant and some responses
housing	Binary	3 levels, no significant difference in association for three different groups
loan	Binary	4 levels, no significant difference in association for three different groups
contact	Catagorical	2 levels, responses from cellular contact is higher
day_of_week	Catagorical	5 levels, response from customer is better on Wed,Thu, Tue
month	Catagorical	10 levels, there is significant variations of responses from Customers
duration	Numeric	closely associated with response variable with threshold for positive respons
campaign	Numeric	Number of campaign has impact on positive response of the campaign
pdays	Numeric	This variable does not seem to have strong relationship with response varial
previous	Numeric	previous contacts seems to have influence on the positive response of the ca
poutcome	Catagorical	have relationship with campaign outcome, earlier success has better respons
emp.var.rate	Numeric	lower the variation rates higher the number of positive outcome
cons.price.idx	Numeric	lower consumer price index seems to have higher positive response rate
cons.conf.idx	Numeric	lower confidence index brings more success to the campaign as people tend
euribor3m	Numeric	lower rate has association with more number of positive cases
nr.employed	Numeric	lower the number of employee higher the number of positive responses

101 5.1.4 Missing values

102 We see that there are no missing values in our dataset.

103 5.1.5 Proportion of Response Variables

104 **Data Preparation**

105 -Convert Binary to 0 and 1 -Create dummy variables -Data Summary Analysis

106 -Correlation of Variables with y

107 Convert Binary yes and no to 0 and 1

Now in order to prepare the data for modeling, we need to update Yes = 1 and No = 0.

Create dummy variables

Now we need to create dummy variables to find out the relationship between y variables and dependent variables, for all categorical variables.

Prepare test data

We will treat the test data the same way as the train data, and then apply models created using the treated train data.

Data Summary with Dummy variables

Correlation between Response and Predictor of Variables Now we will produce the correlation table between the independent variables and the dependent variable

Outlines Handling

Analysis the link function for given variables

In this section, we will investigate how our initial data aligns with a typical logistic model plot.

Recall the Logistic Regression is part of a larger class of algorithms known as Generalized Linear Model (glm). The fundamental equation of generalized linear model is:

g(E(y)) = a+ Bx1+B2x2+ B3x_3+...

where, g() is the link function, E(y) is the expectation of target variable and B0 + B1x1 + B2x2+B3x3 is the linear predictor B0,B1,B2, B3 to be predicted. The role of link function is to "link" the expectation of y to linear predictor.

In logistic regression, we are only concerned about the probability of outcome dependent variable success or failure. As described above, g() is the link function. This function is established using two things: Probability of Success as p and Probability of Failure as 1-p. p should meet following criteria: It must always be positive (since p >= 0) It must always be less than equals to 1 (since p <= 1).

Now let's investigate how our initial data model aligns with the above criteria. In other words, we will plot regression model plots for each variable and compare it to a typical

logistic model plot:

The main objective in the transformations is to achieve linear relationships with the dependent variable or, really, with its logit.

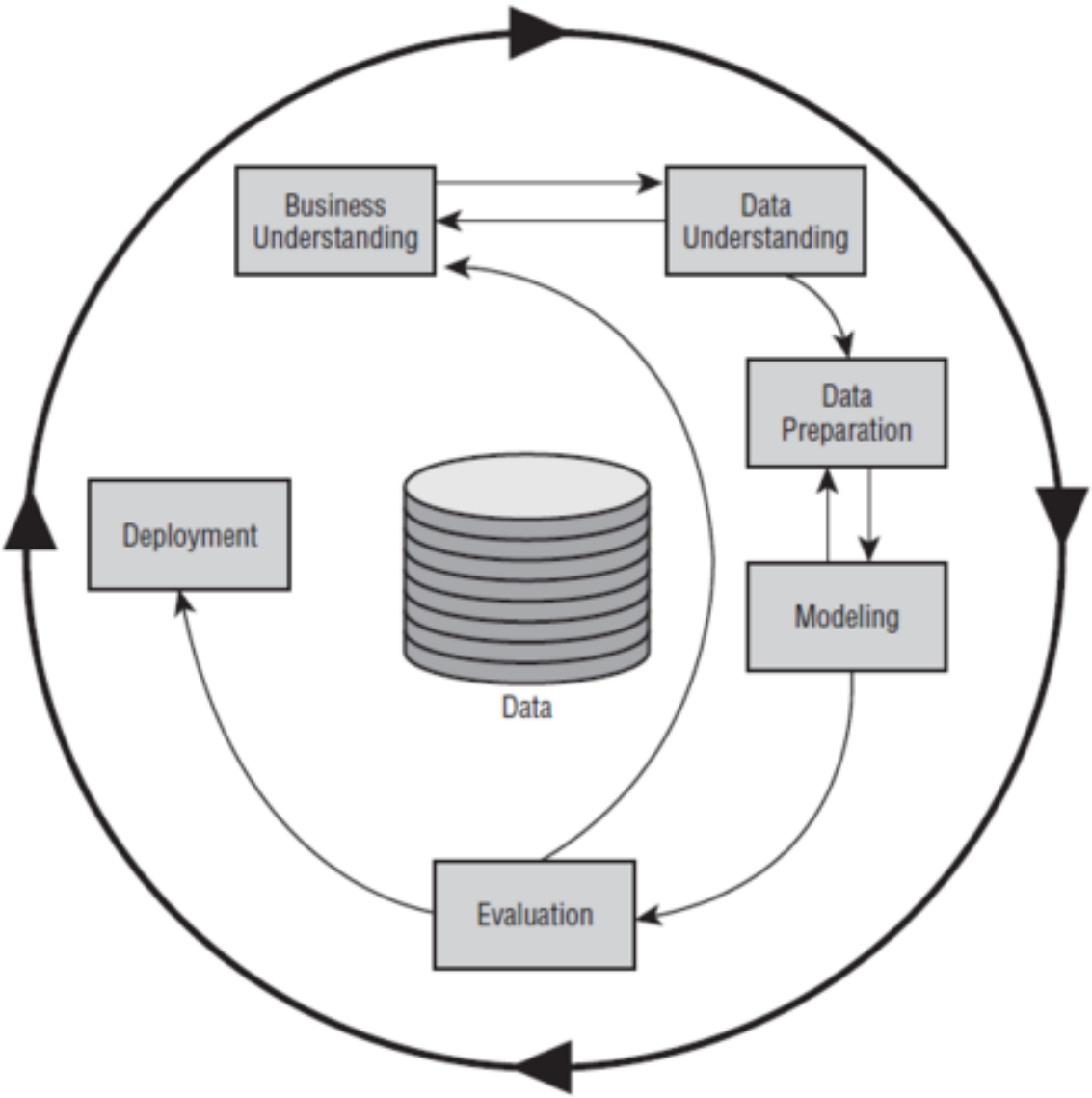


Figure 1. CRISP-DM

Modeling:

Logistics Regression:. Logistic Regression is a probabilistic statistical classification model. It is also used to predict a binary response from a binary predictor.Logistics model

doesn't suffer a lot from severe class imbalance. Logistic Regression creates log odds of the response as a linear function of predictor variables. Many of the categorical predictors in the data set for this project have sparse and unbalanced distributions. Using logistics model with the given set of data would need adjustment of variables to fine tune the model.

Classification Tree. Classification Tree is used to predict the outcome of a categorical response variable.The purpose of the analyses via tree-building algorithms is to determine a set of logical conditional split that permit accurate classification of cases and accurate prediction.Effectiveness of classification tree model with binary variable is one of the reason for selection for this analysis study. This model though has problem with over fitting. We will also create RandomForest model to overcome that.

RandomForest Model. Random Forests grows many classification trees for given set of response and predictor variables. Each tree gives a classification, and all the outputs from different trees are "votes" for that class. The forest chooses the classification having the most votes (over all the trees in the forest). Over fitting problem with the classification tree can be overcome by this approach with weighted average of more number of trees. This method is good for prediction but a little bit difficult to interpret. Since we are facing the binary category,Random Forest is a good classification method to try.

Evaluation

There are number of ways to evaluate the regression and classification models based on the purpose like prediction, classification, variable selection etc. In the given business scenario objective is to classification of the response variable by building a model that can predict likelihood of response from Customer. Following evaluation criteria we have used for model evaluation:

(1) The Hosmer-Lemeshow test assesses the model calibration and how predicted values tend to match the predicted frequency when split by risk decides. This test will be used for Logistics regression model validation.

(2) AUC along with Model Accuracy will be used for model evaluation. Accuracy is calculated based on certain threshold where as AUC is overall performance evaluation of model as various points.AUC criteria will be given more weight age for model evaluation in this case.

Experimentations:

In this section experimentation will be carried out with the data by formulating three different types of models with three different approaches. Following are the three different approaches that will be used here-

-Model 1- This model will be created by using logit function of Generalized Logistics Model(GLM).

-Model 2: This model will be created by using Classification tree function.

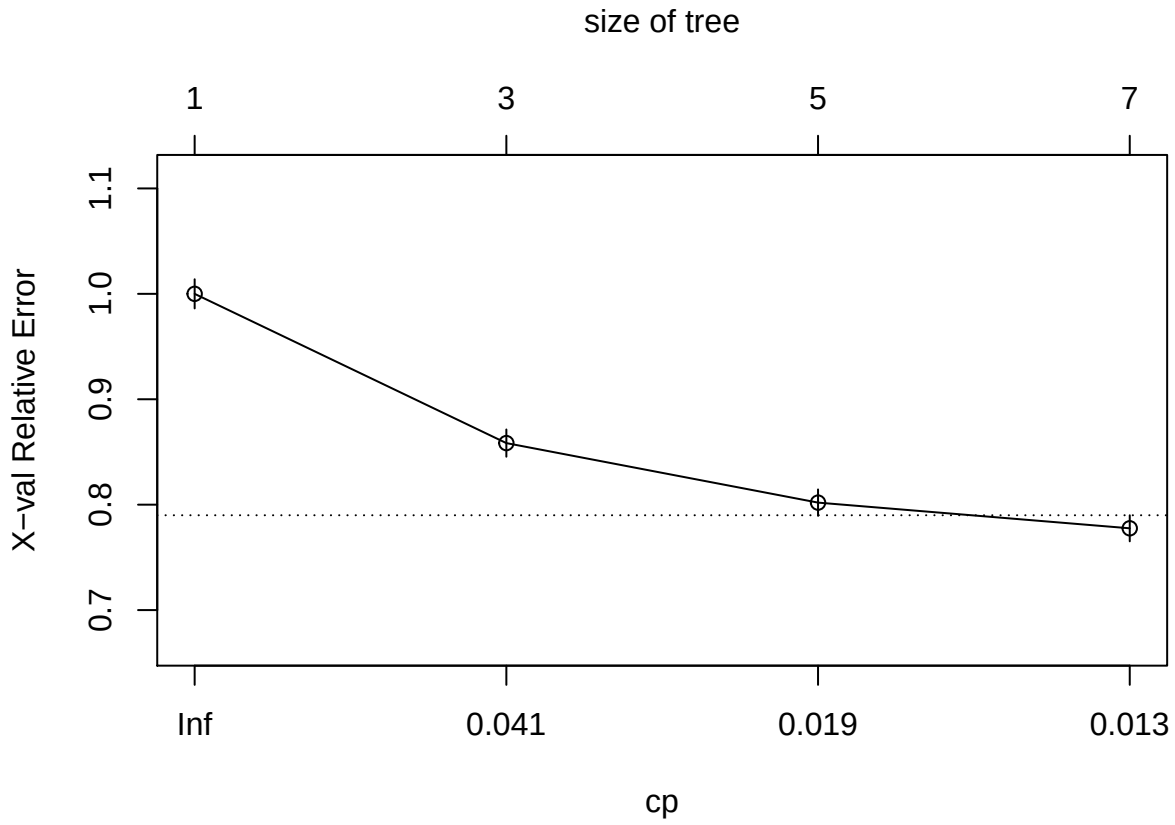
-Model 3- This model will be created by using classification technique RandomForests model.

There are two data set given with the business case training and test set. Training set will be used to train the model and the test set will be used to evaluate the model performance.

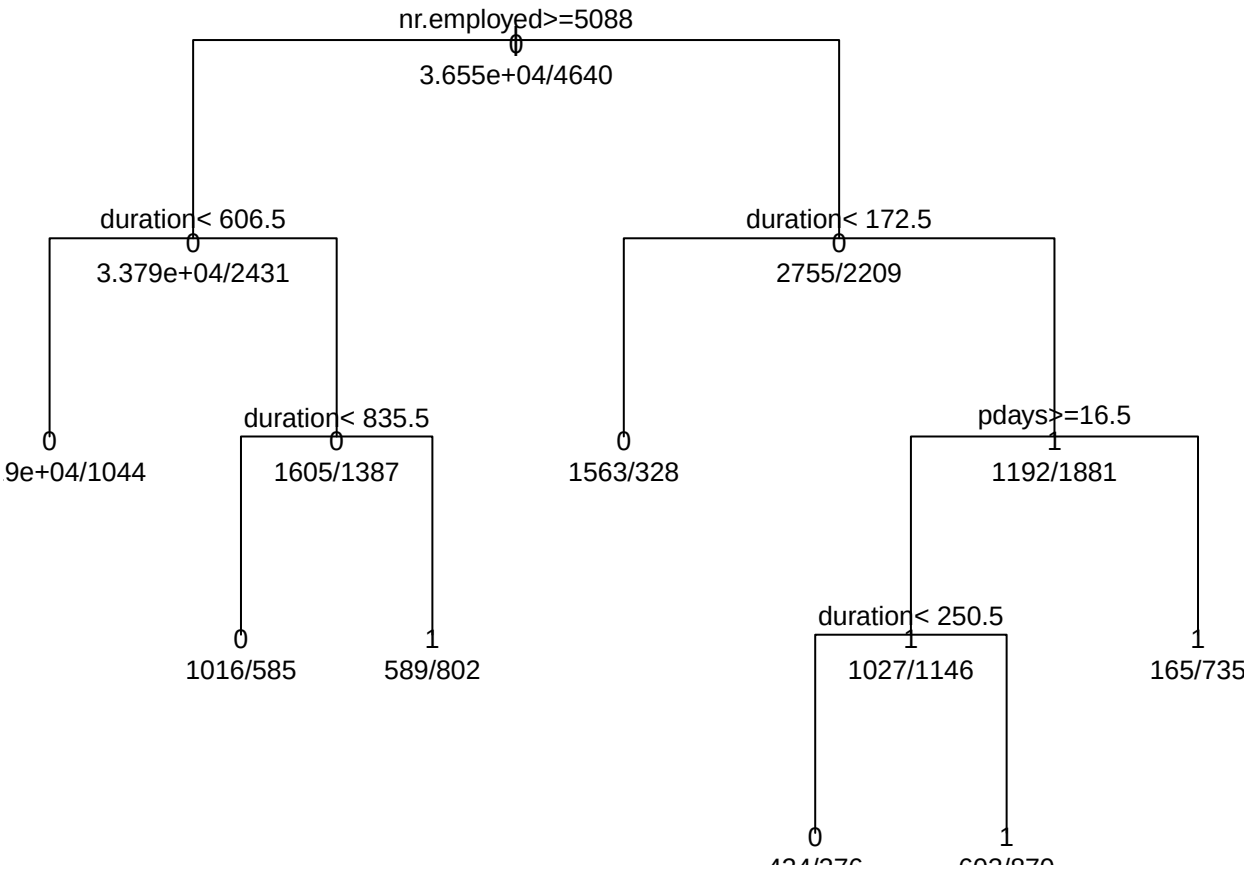
Logistics Regression- Model 1. Logistics regression function GLM has been used to classify the campaign response variable. Basic model generated by using GLM function has been enhanced by making necessary adjustments to non associated predictor variables shown as "NA" in basic model output. Next the model has been validated by using k=5 fold cross validation press to do necessary adjustment to the model.

There were total 10 iterations been performed before final selection of variables were made. AIC value from model 1 and model1_update(enhanced) model were same 13776. Hence removing variables from basic model does not help performance wise but reduced complexity with less degrees of freedom.By using k=5 cross validation, ($delta) error value came out to be low 0.06289177.

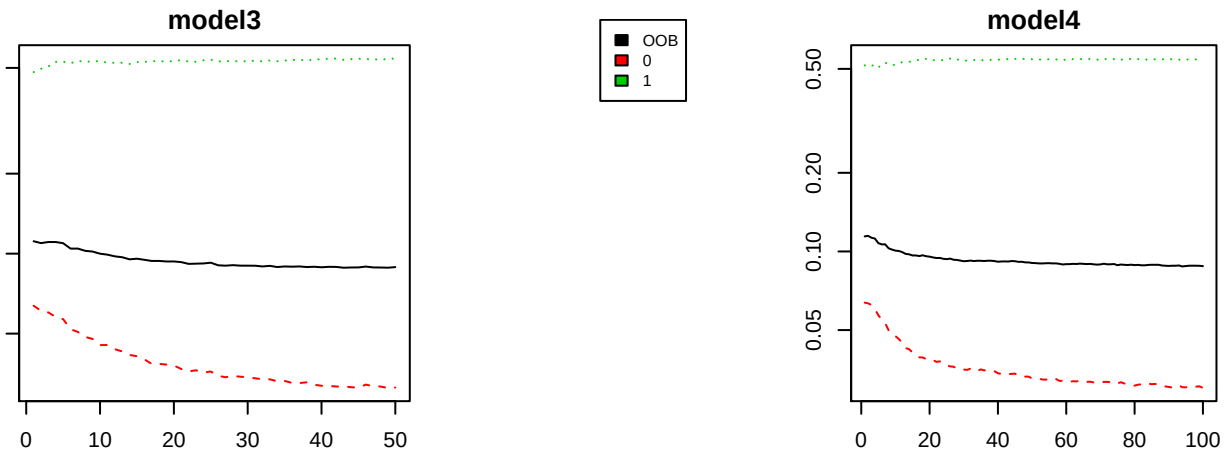
Classification Tree- Model 2. The basic idea of classification tree model is to predict a response variable y for the campaign from predictor variables. Model does this by growing a binary tree. At each node in the tree, a test is applied to one of the inputs. Depending on the outcome of the test two routes to be followed left or right. Eventually a leaf node is reached where a prediction is made about the binary outcome of campaign response. Model 2 has been rated using the Classification function from ROCR package.Basic model has been optimized using prune function.



Following are the most important variables from this model-duration ,nr.employed ,euribor3m ,emp.var.rate, cons.conf.idx , cons.price.idx.Total 6 leafs(decision points) have been formed from this model. Complete Classification tree is given below in the diagram.

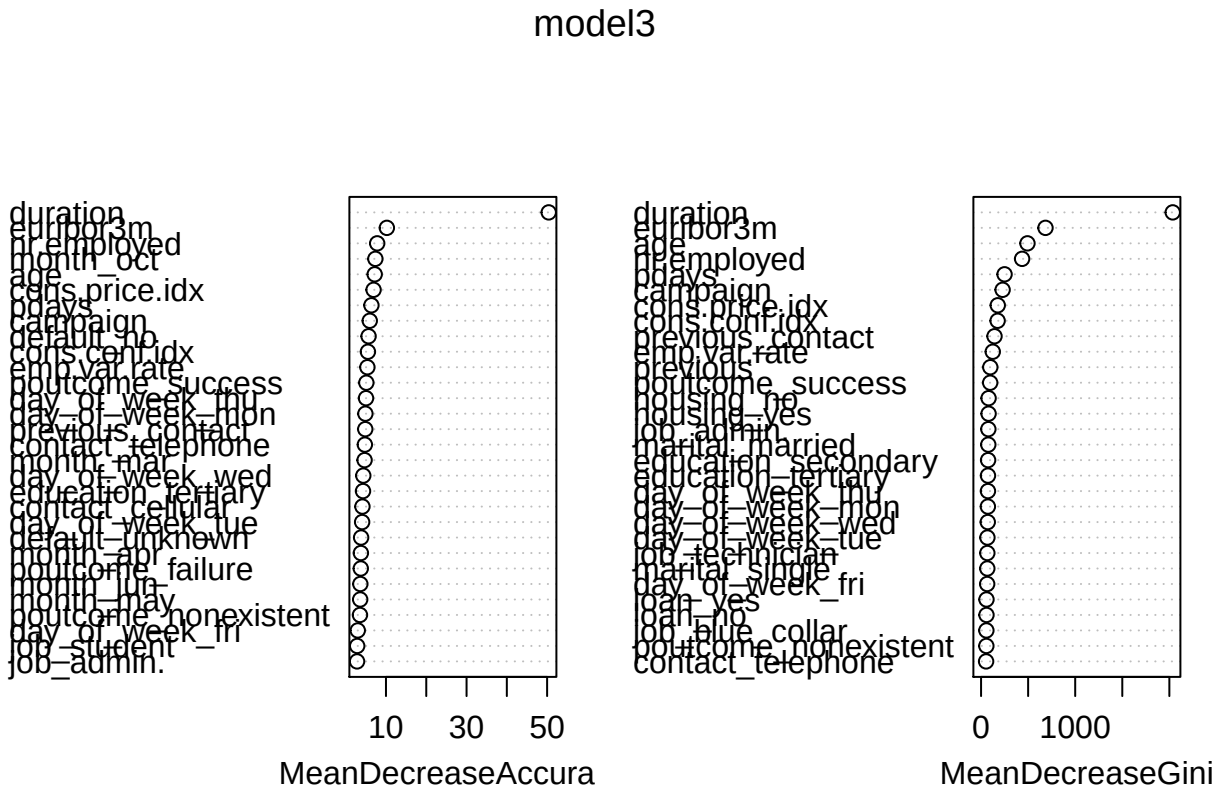


205 **RandomForest- Model 3.** In Random Forests many classification trees are formed
206 to classify campaign response variable y. Each tree creates separate set of classification, each
207 tree is voted for performance for that classification. The forest chooses the classification
208 having the most votes (over all the trees in the forest). One model will be created using this
209 method with tree size 50. Then this model will be evaluated with a model of tree size 100.



From the chart above it can be seen that classification error rate to classify negative responses reduces with the increase in number of trees but there is no significant change in error rate for positive response.There is only slight reduction in error rate for negative responses when tree size is increased to 100 from 50.Number of variables tried at each split are 7 with negative classification rate of 0.03 and positive classification error rate of 0.51.

Below chart provides importance of various variables used in the model.



Results from Models:

Results from Regression Model: Logistics Regression model has a very high accuracy rate of 91.42% when model was evaluated using the validation data set. Though the AUC value for this model was comparatively lower 0.702 which indicates not good fitment of the model. By using Hosmer-Lemeshow goodness-of-fit (GOF) tests when model was evaluated p value came to be greater than 0.05. With this test if the p value is lower than 0.05 model is rejected and if it's high, then the model passes the test. Regression model passed this test.

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Hosmer and Lemeshow goodness of fit (GOF) test
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data: model1_update$y, fitted(m) X-squared = 14.926, df = 8, p-value = 0.0606

Results from Classification Tree Model-this model has also very high accuracy rate of 91.81% which is very good.This model has AUC value of 0.865 which seem to be inline with given high accuracy.

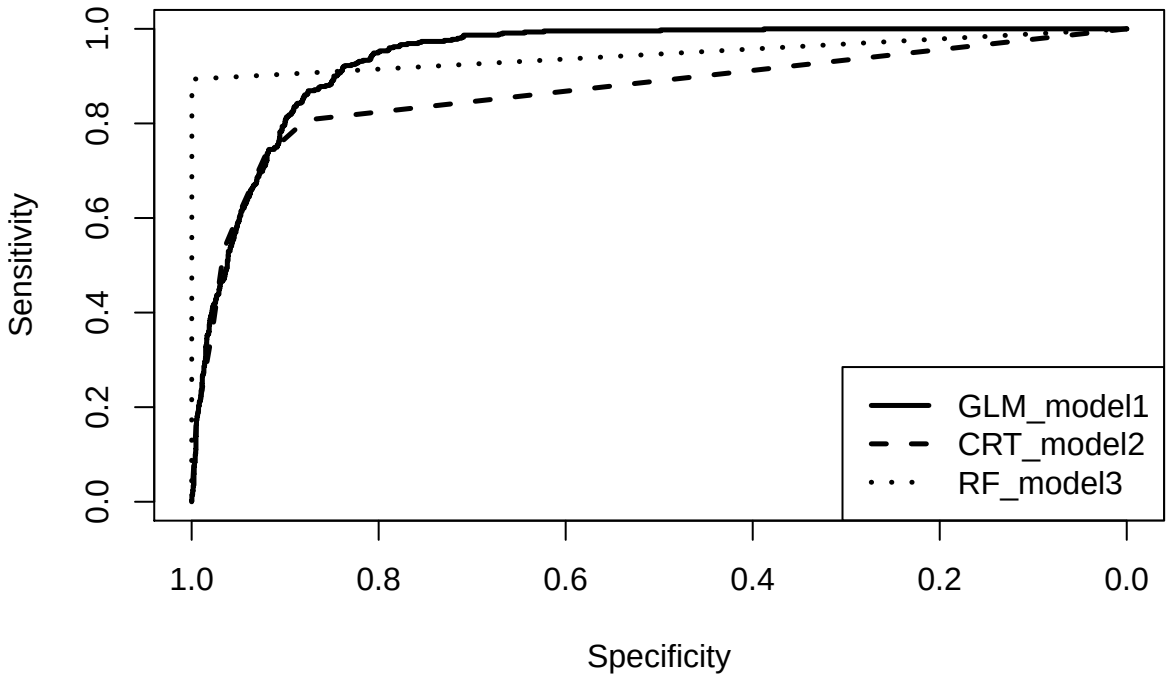
Results from RandomForest Model-The model created using Randomforest has accuracy of 98.64% which is extraordinary results and give rise to suspicion model is able to separate out the classification based on certain variable. When we looked at the importance of variable "duration" it becomes apparent that this variable is being used in a big way to classify response accurately. It can be seen that this model also shows the similar kind of trend in classification of data in earlier stages with very stiff line till true positive rate of 0.4 and then sharp increase in false positive rate.

Discussion and Conclusions:

Table 2

Comparison of 3 Model3

	Model	Accuracy	Error_Rate	Precision	sensitivity	specificity	F1_Score	AUC
1	GLM	0.9142996	0.0857004	0.4323725	0.6678082	0.9331069	0.3607211	0.7029638
2	CRT	0.9181840	0.0818160	0.5343681	0.6548913	0.9440149	0.4377405	0.8650875
3	RF	0.9881039	0.0118961	0.8935698	0.9975248	0.9870794	0.8982729	0.9466486



238

239 $ Final model selection:

240 Based on the Accuracy of the model, model 1 and model 2 are very close around 91%
241 accuracy with probability threshold of 0.5. Model 3 has much higher value of 98%. But
242 Accuracy is not always the key criteria for a model as Accuracy is calculated based on a
243 defined threshold. Also due to imbalance of data o 10% to 90% distribution of response
244 variable forced to choose the model based on other criteria. Model Based on AUC value is
245 model 3 having AUC value of 0.9398 which is a very good score. Model 3 stands out among
246 the three models.

247 $ Key predictor variables:

248 For all three models it is found variables “duration” is most important variables by far.
249 This variable has positive impact in campaign outcome. This could be due to the fact that
250 longer the Customer stays on phone more productive conversation is taking place to get the
251 Customer start their term deposit Account. “euribor3m” is most important variable which

denotes inter bank interest rate in Eurozone. Term deposit interest rates are generally interlinked and tends to go up together. This variable has positive impact on response variable. Predictor "nr.employed" denotes number of employees for the bank. This variable also has positive impact on campaign response. More the number of employees more visible the bank is and in turn more customers it gets through the campaign.

Among the negative variables "emp.var.rate" has negative impact on response. As negative rate of this variable indicates issues with economy and lower economic activities. That in turn could impact the savings rate and people tend to use their savings that time.

$ Shortcomings :

Imbalance of response variable only 10% of population was the main shortcomings that we have in the model creation. This issue has been addressed partially by using Area Under Curve as the criteria for model selection.

$ Final Recommendation :

In conclusion it can be suggested to the bank management that focus should be given in hiring more people, doing more quality phone calls. Also to time the campaign in a stable macroeconomic environment to get better return on investment from this campaign.

References

be sure to cite all references used in the report (APA format). We used R (3.2.2, R Core Team, 2016) and the R-packages *papaja* (0.1.0.9054, Aust & Barth, 2015), *papaja* (0.1.0.9054, Aust & Barth, 2015), *Amelia* (1.7.4, Honaker, King, & Blackwell, 2011), *aod* (1.3, Lesnoff, M., Lancelot, & R., 2012), *AUC* (0.3.0, Ballings & Poel, 2013), *boot* (1.3.18, Davison & Hinkley, 1997), *dplyr* (0.4.3, H. Wickham & Francois, 2015), *faraway* (1.0.7, Faraway, 2016), *gdata* (2.17.0, Warnes et al., 2015), *ggplot2* (2.0.0, H. Wickham, 2009), *gplots* (3.0.1, Warnes et al., 2016), *gridExtra* (2.2.1, Auguie, 2016), *ISLR* (1.0, James, Witten, Hastie, & Tibshirani, 2013), *knitr* (1.12.3, Xie, 2015), *leaps* (2.9, Fortran code by Alan Miller, 2009), *MASS* (7.3.43, W. N. Venables & Ripley, 2002), *popbio* (2.4.3, Stubben & Milligan, 2007),

psych (1.5.8, Revelle, 2015), *randomForest* (4.6.12, A. Liaw & Wiener, 2002), *Rcpp* (0.12.5, Eddelbuettel & François, 2011), *reshape* (0.8.5, Wickham & Hadley, 2007), *ResourceSelection* (0.2.6, Lele, Keim, & Solymos, 2016), *ROCR* (1.0.7, Sing, Sander, Beerenwinkel, & Lengauer, 2005), *rpart* (4.1.10, Therneau, Atkinson, & Ripley, 2015), *stringr* (1.0.0, H. Wickham, 2015), and *xtable* (1.8.2, Dahl, 2016) for all our analyses.

Appendix

Supplemental tables and/or figures. R statistical programming code.

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{r
code=readLines(knitr::purl('https://raw.githubusercontent.com/kishkp/data621-ctg5/mast
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6.1 Data Analysis details

6.1.1 Variable Description

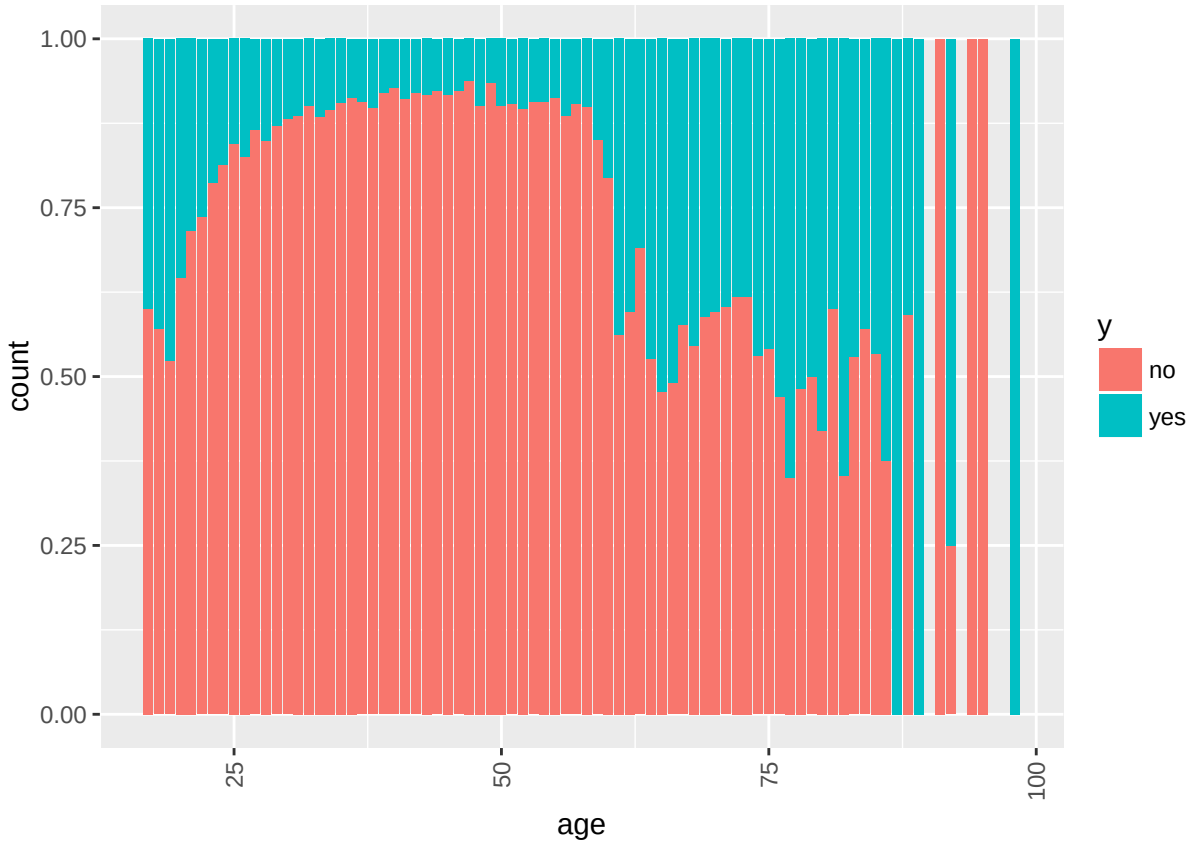
Table 3

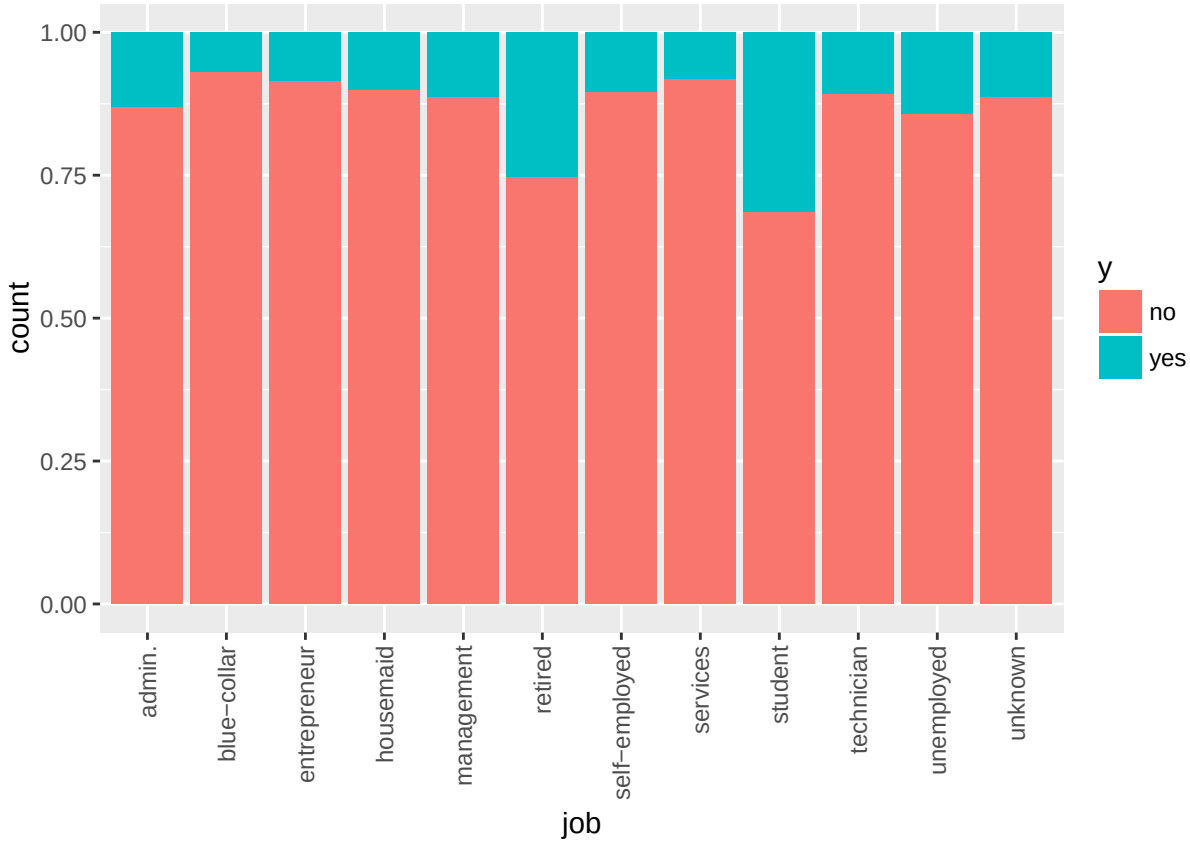
Variable Description

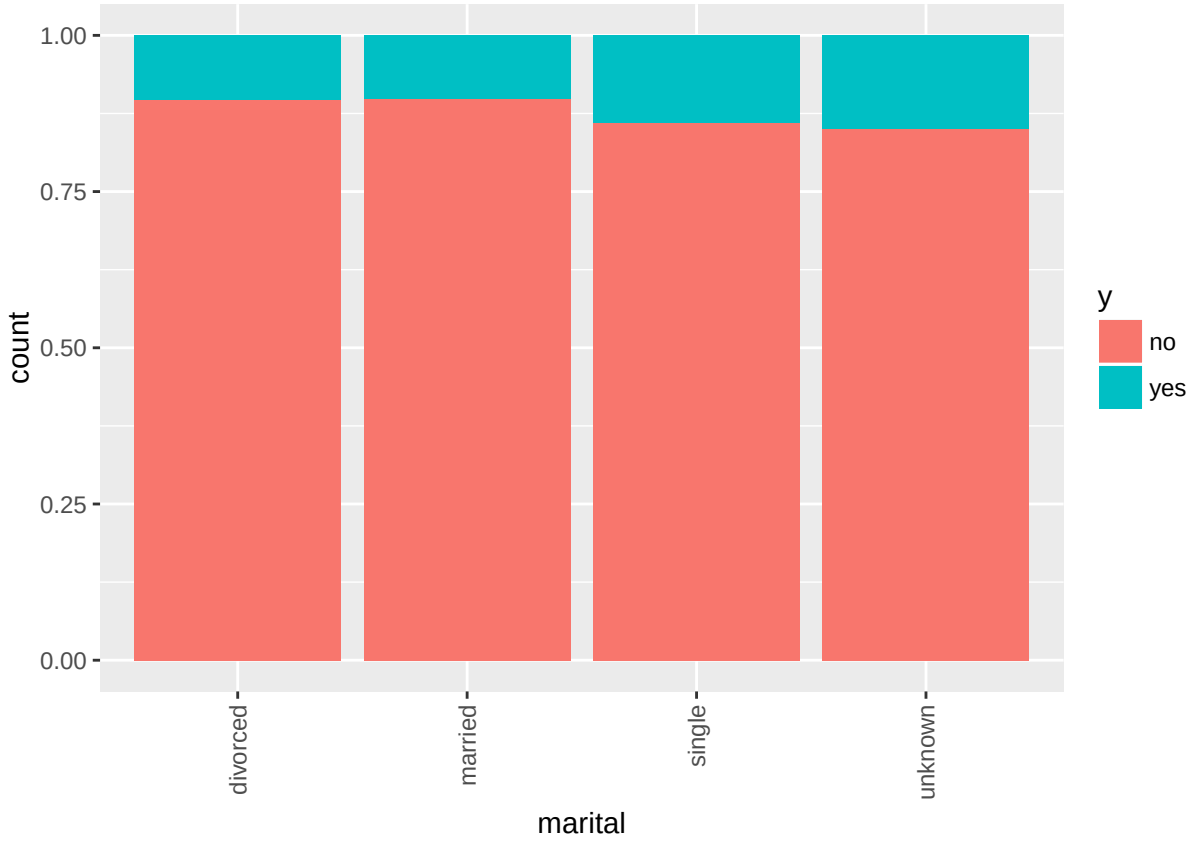
Variable	Data.Type	Type	Description
age	Numeric	Predictor	Client's age
job	Catagorical	Predictor	Client's job
marital	Catagorical	Predictor	Client's marital status
education	Catagorical	Predictor	Client's education level
default	Binary	Predictor	Credit in default?
balance	Numeric	Predictor	Client's average yearly balance, in euros
housing	Binary	Predictor	Client has housing loan?
loan	Binary	Predictor	Client has personal loan?
contact	Catagorical	Predictor	Client's contact communication type

Variable	Data.Type	Type	Description
day	Catagorical	Predictor	Client last contact day of the month
month	Catagorical	Predictor	Client last contact month of year
duration	Numeric	Predictor	Client last contact duration, in seconds
campaign	Numeric	Predictor	Client number of contacts performed during this campaign
pdays	Numeric	Predictor	Client days that passed after first contact
previous	Numeric	Predictor	Number of contacts performed before this campaign
poutcome	Catagorical	Predictor	Outcome of the previous marketing campaign
emp.var.rate	Numeric	Predictor	Quarterly employment variation rate
cons.price.idx	Numeric	Predictor	Monthly consumer price index
cons.conf.idx	Numeric	Predictor	Monthly consumer confidence index
euribor3m	Numeric	Predictor	Daily euribor 3 month rate
nr.employed	Numeric	Predictor	Quarterly number of employees
y	Binary	Response	Has the client subscribed a term deposit?

6.1.2 Predictor and Response variable Association



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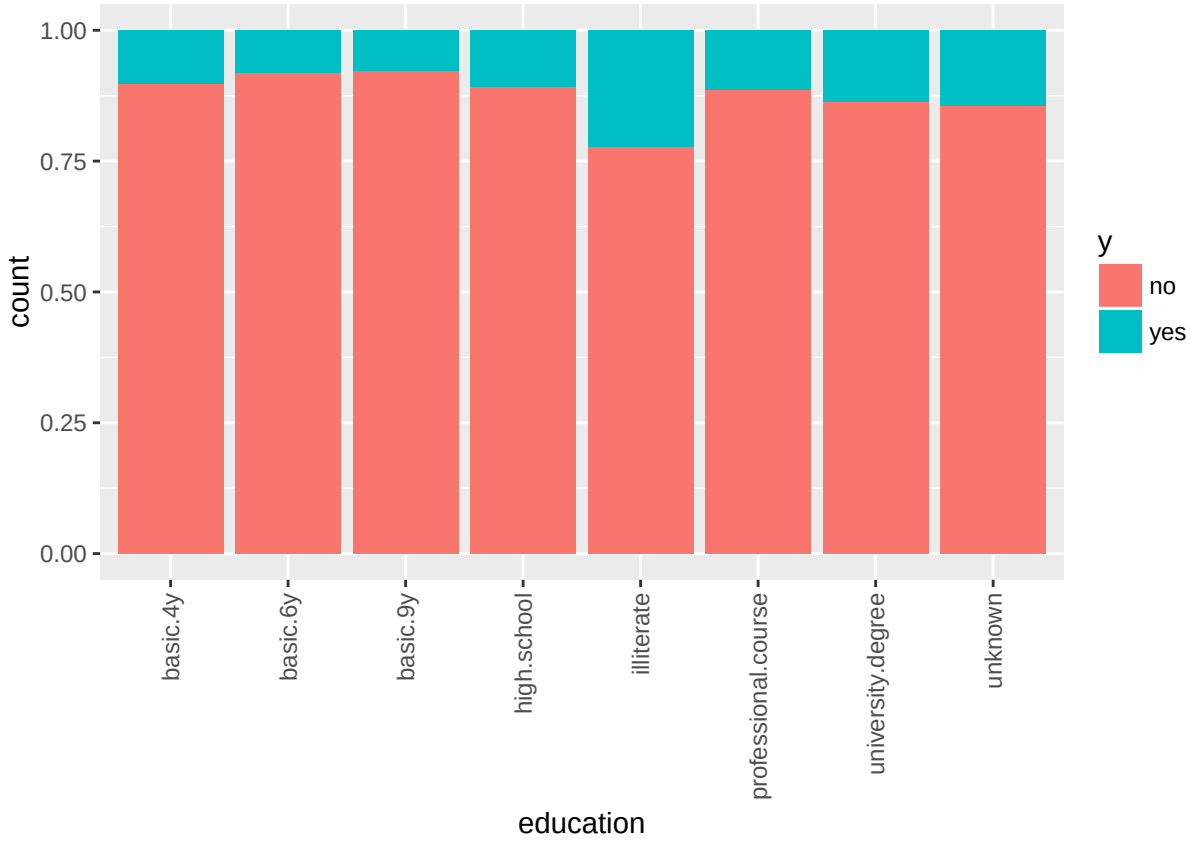
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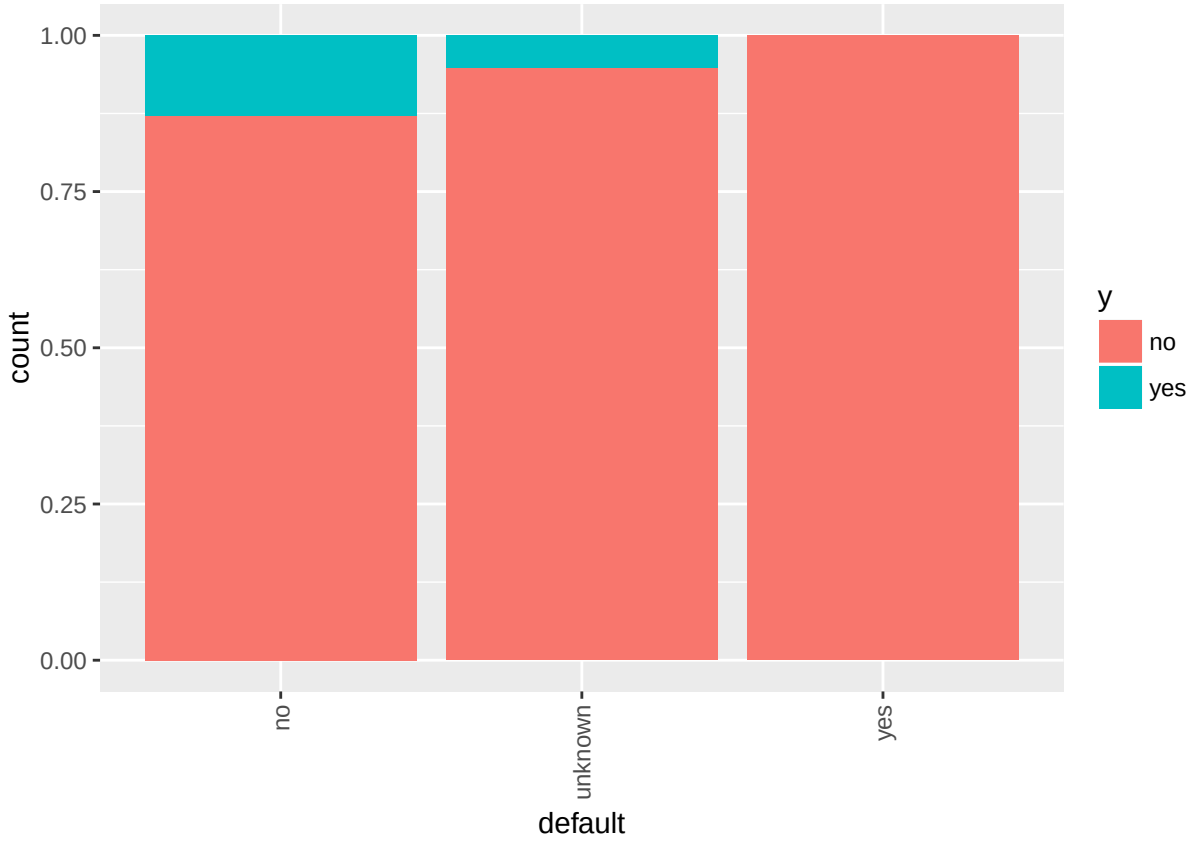

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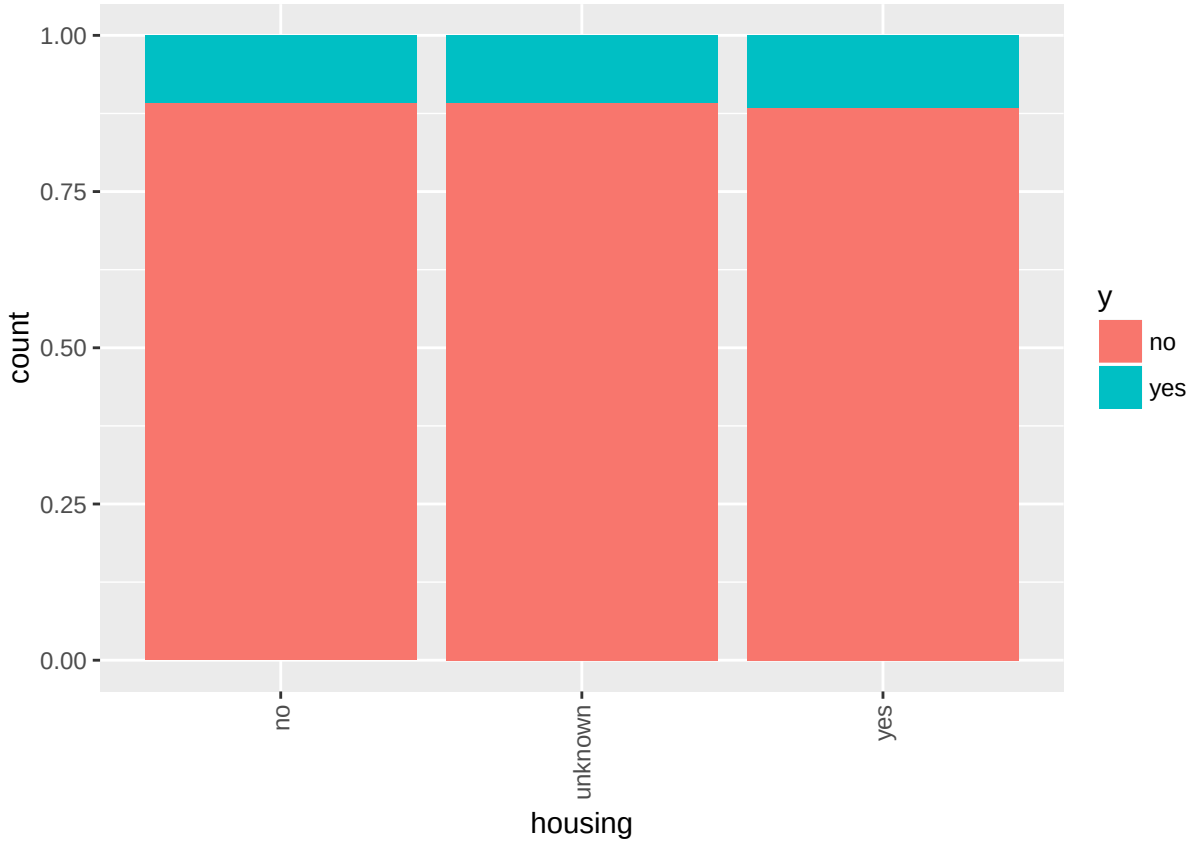

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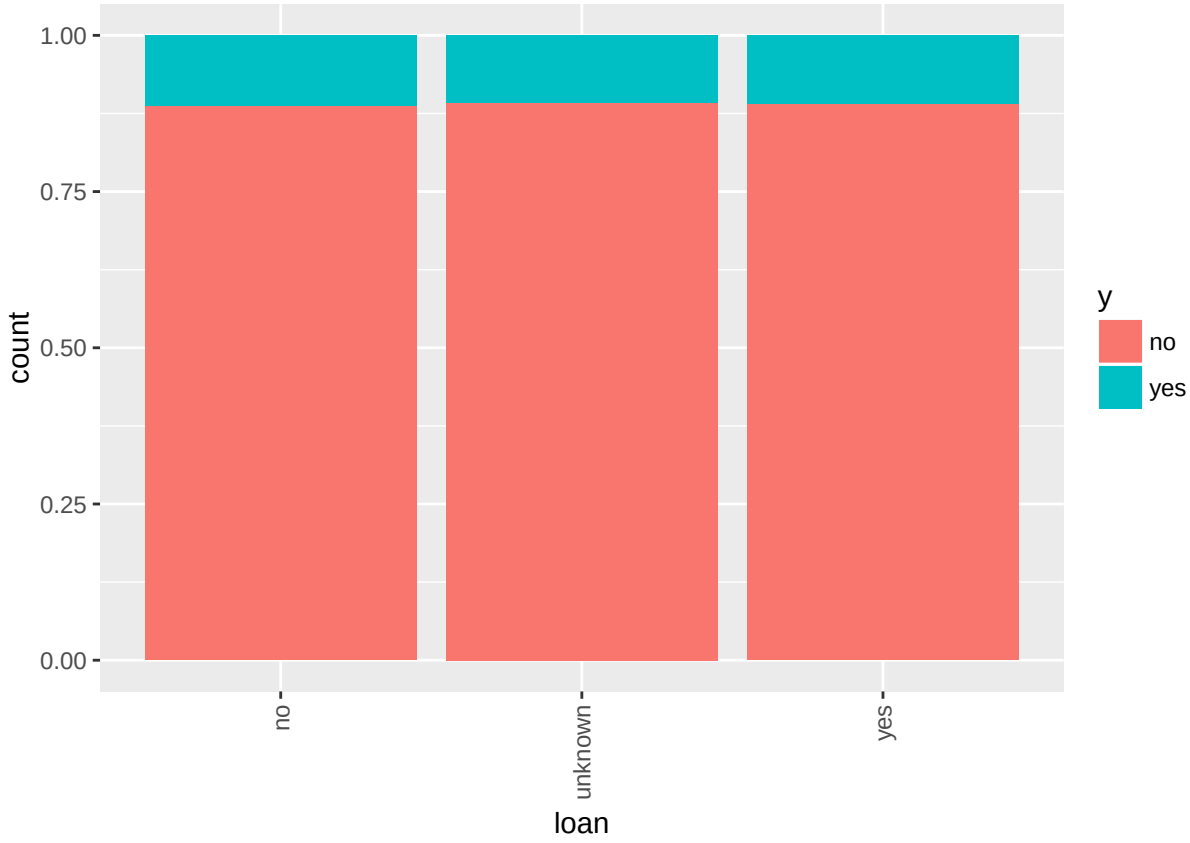

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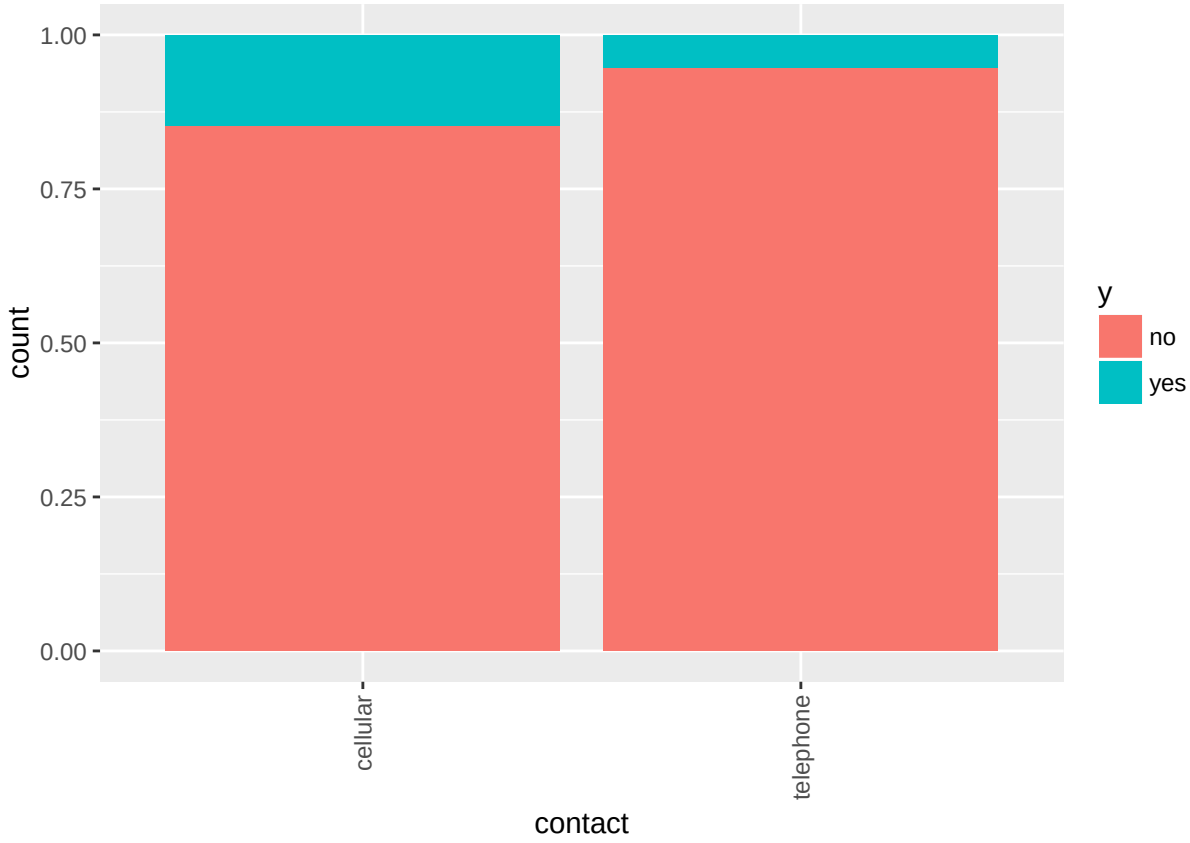
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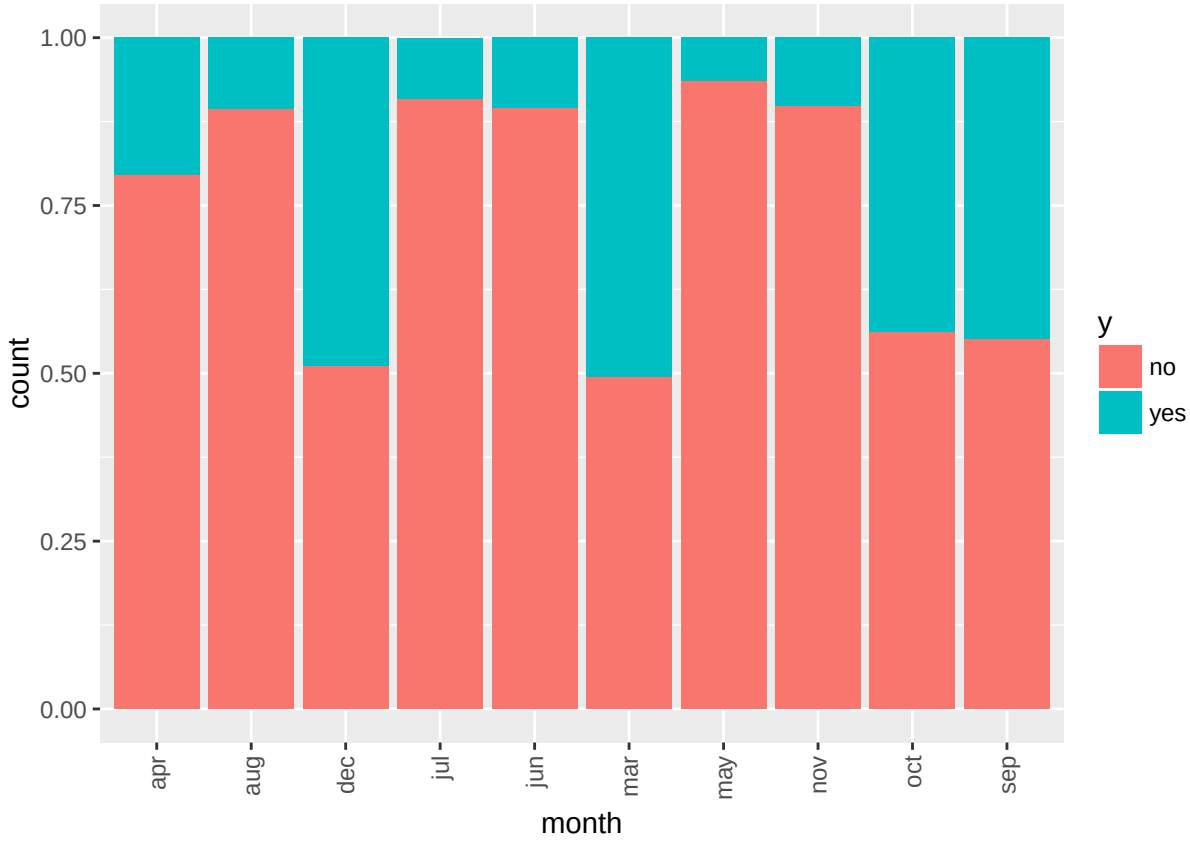
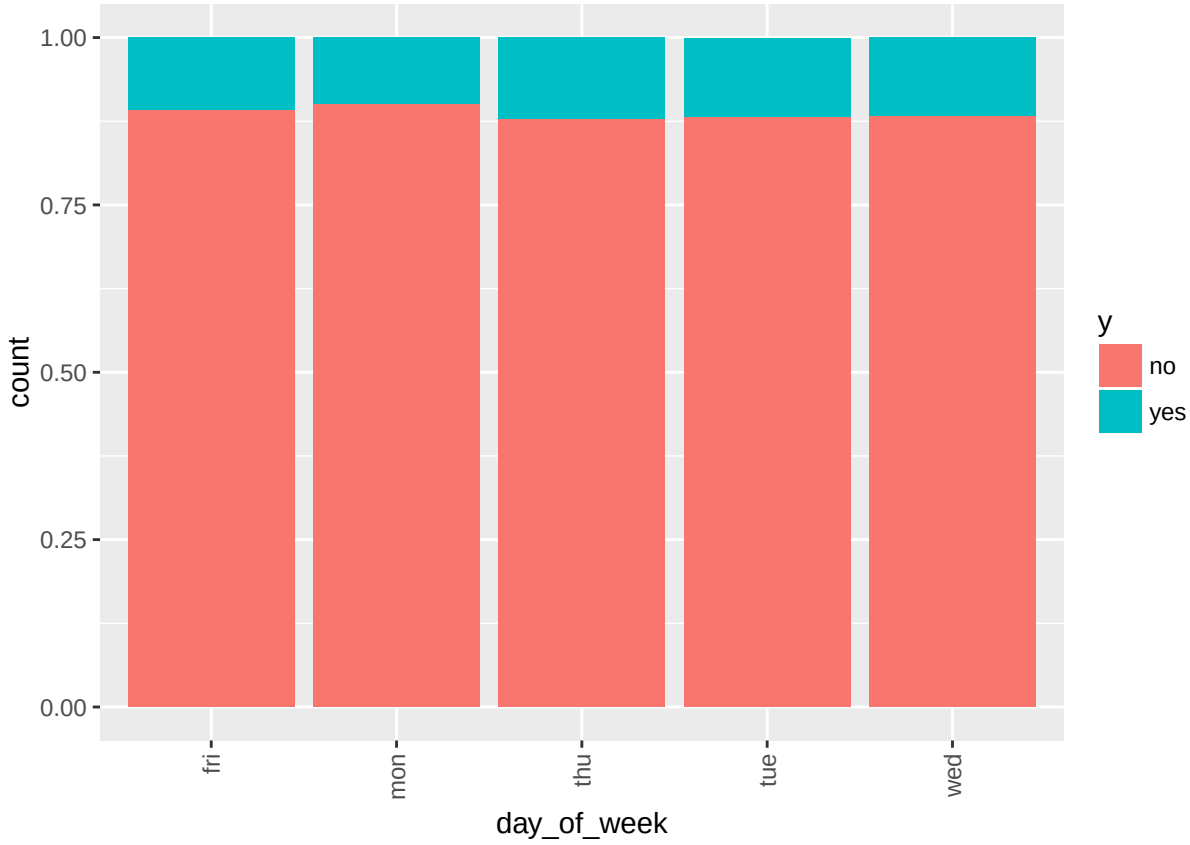
yes

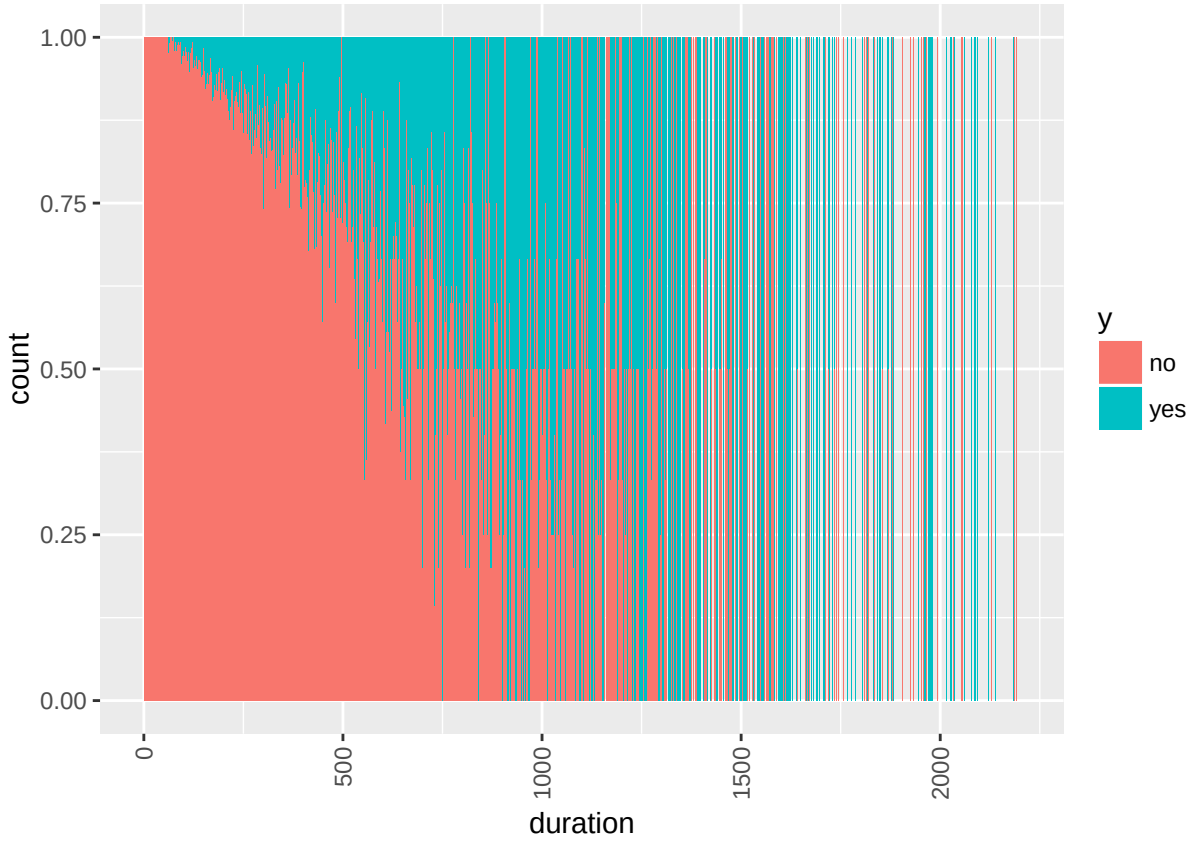
298


1.00
0.75
0.50
0.25
0.00
count
apr
aug
dec
jul
jun
mar
may
nov
oct
sep
month
y
no
yes

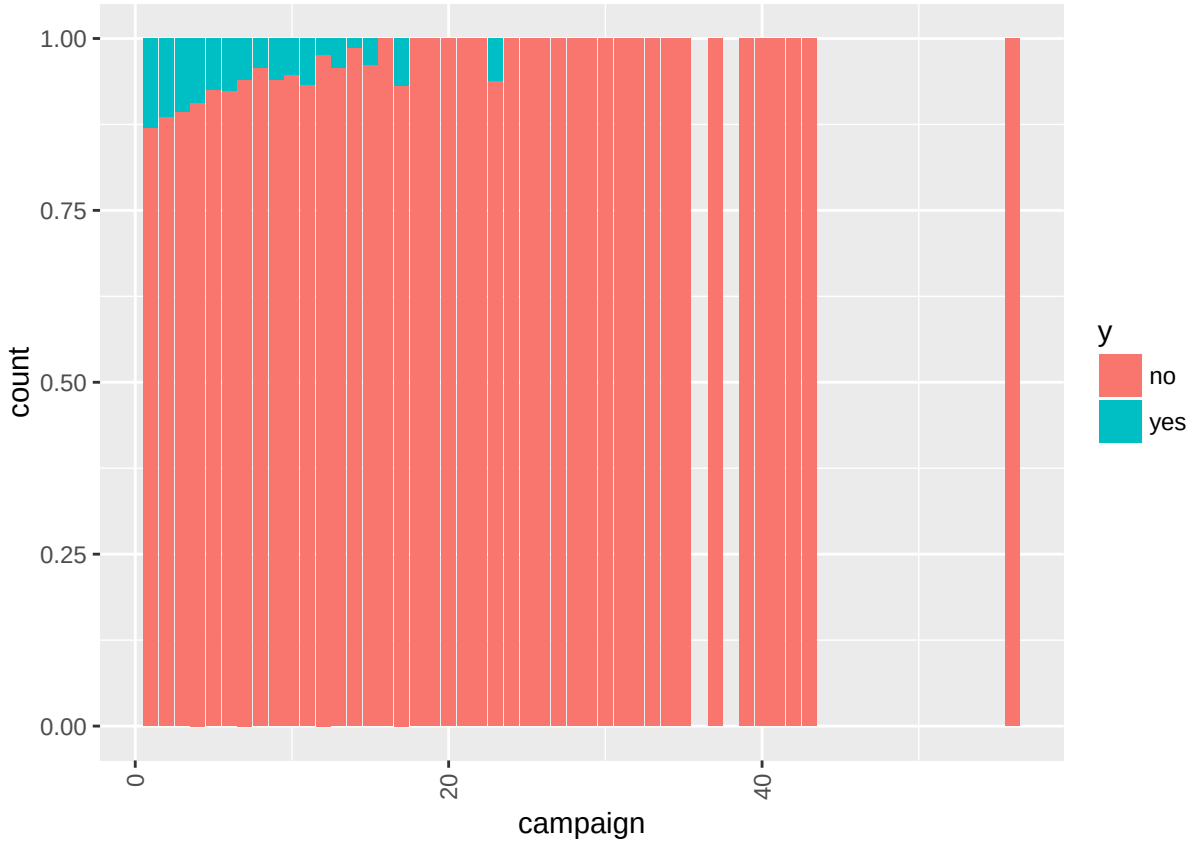
299


1.00
0.75
0.50
0.25
0.00
count
fri
mon
thu
tue
wed
day_of_week
y
no
yes

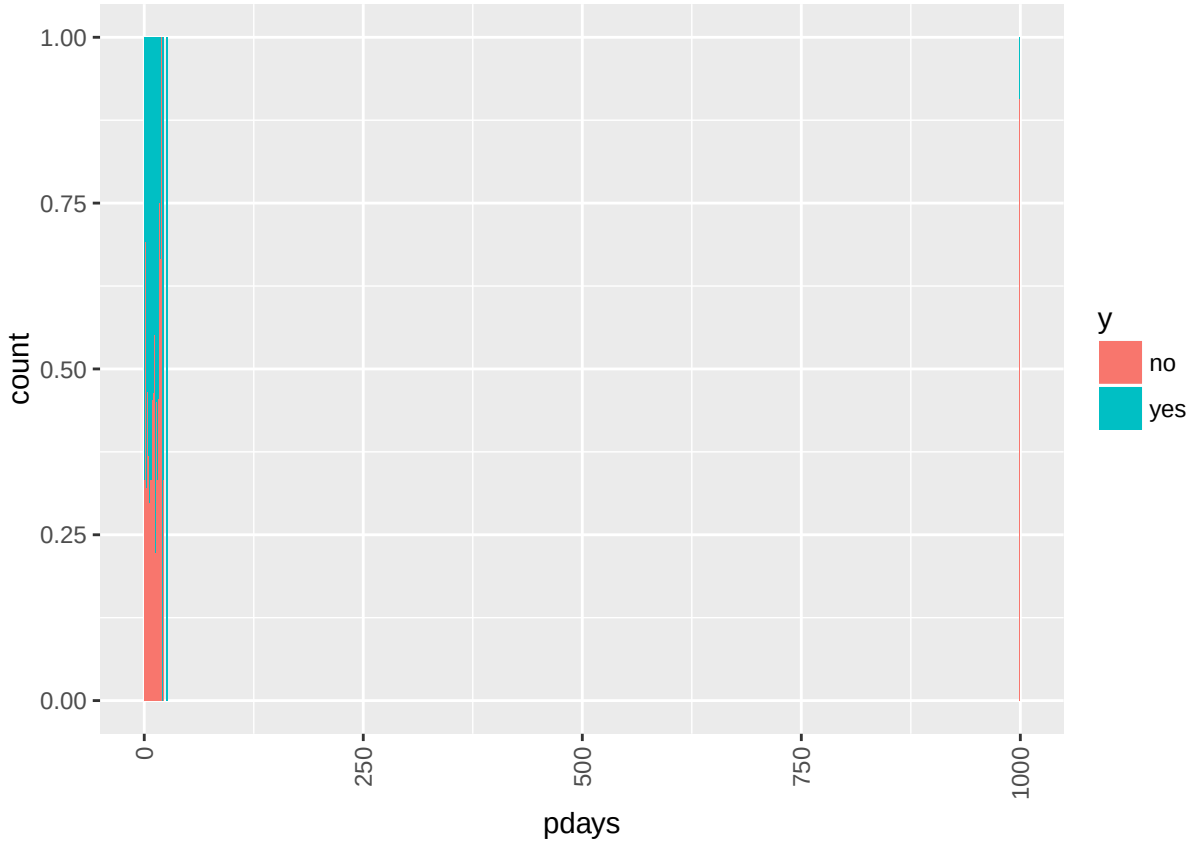
300


1.00
0.75
0.50
0.25
0.00
count
0
500
1000
1500
2000
duration
y
no
yes

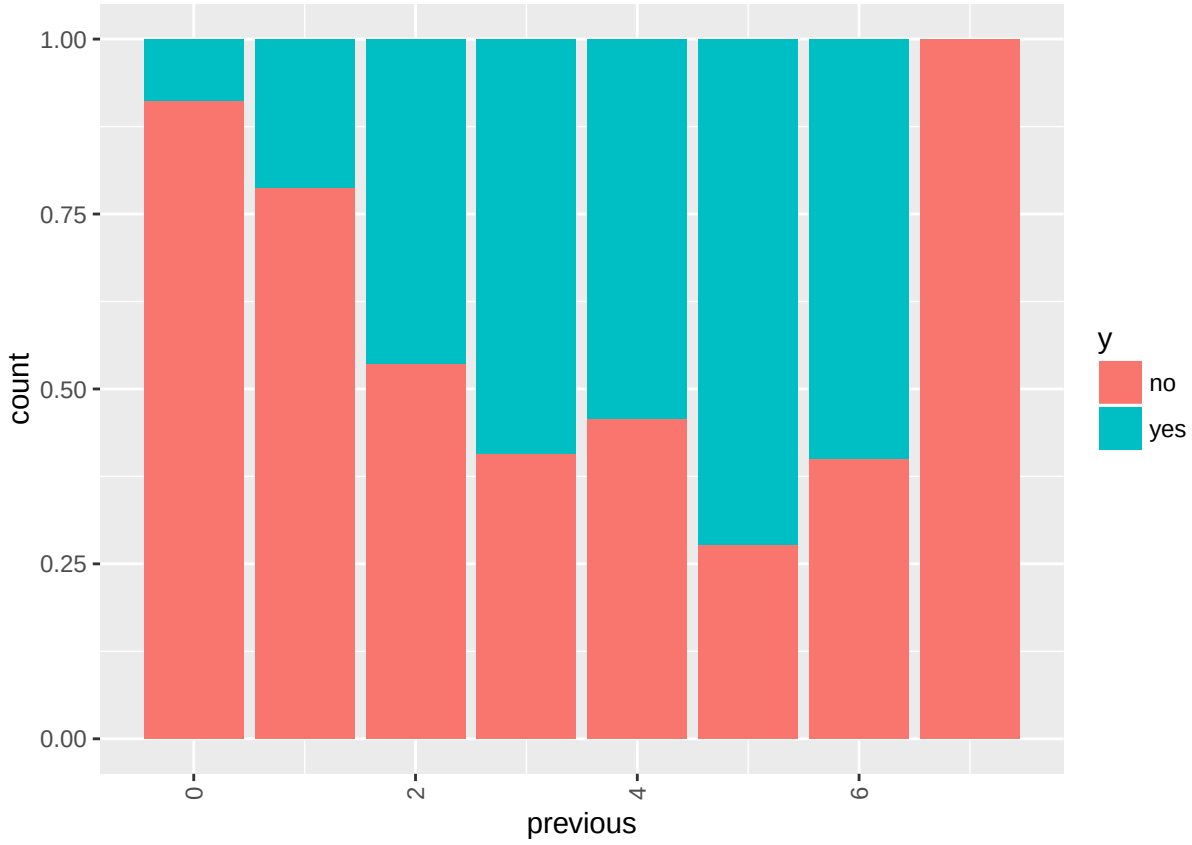
301



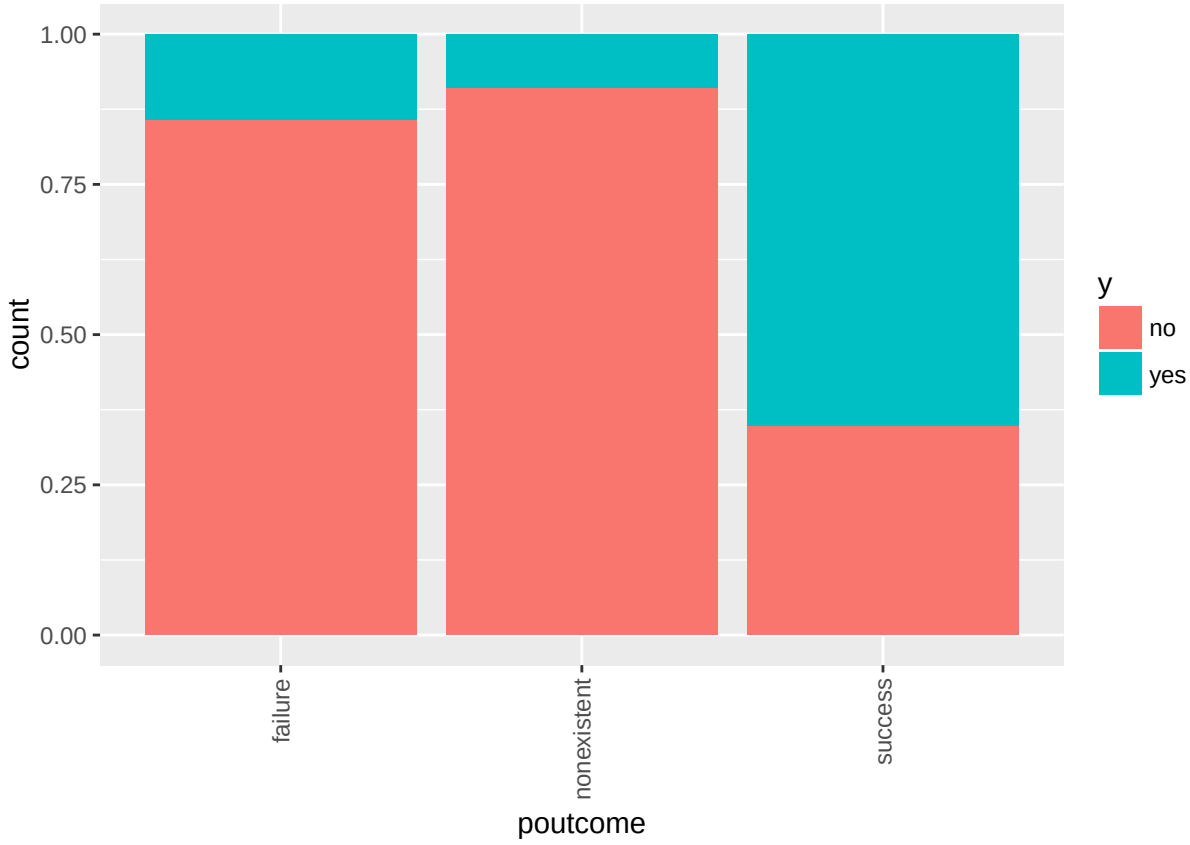
302



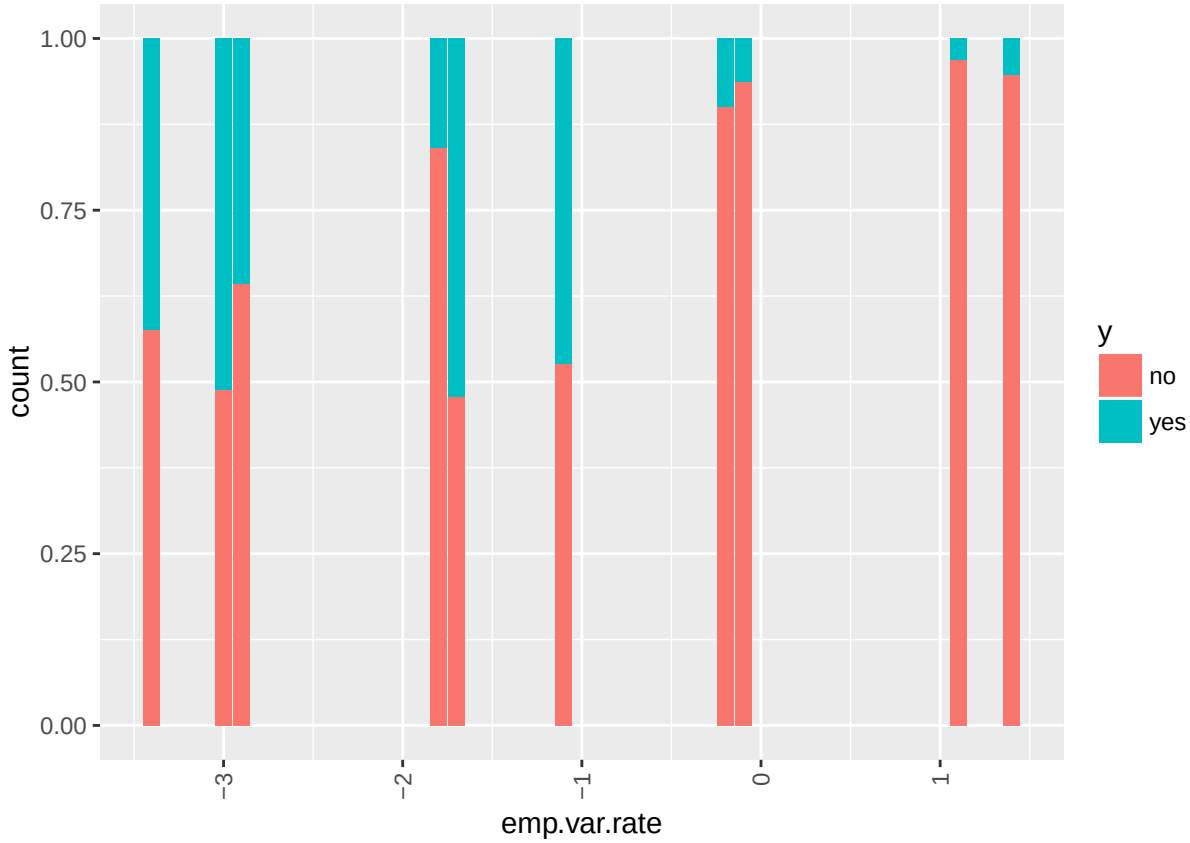
303



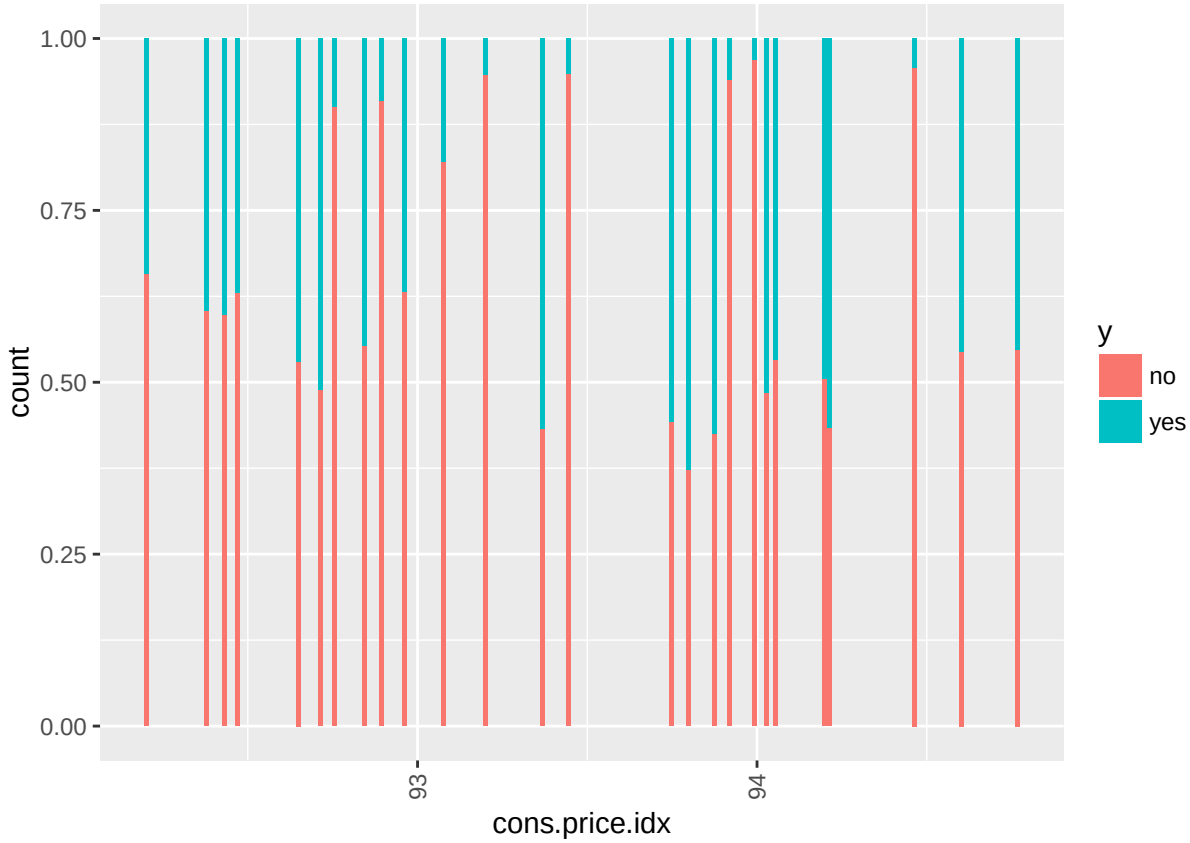
304


1.00
0.75
0.50
0.25
0.00
count
failure
nonexistent
success
poutcome
y
no
yes

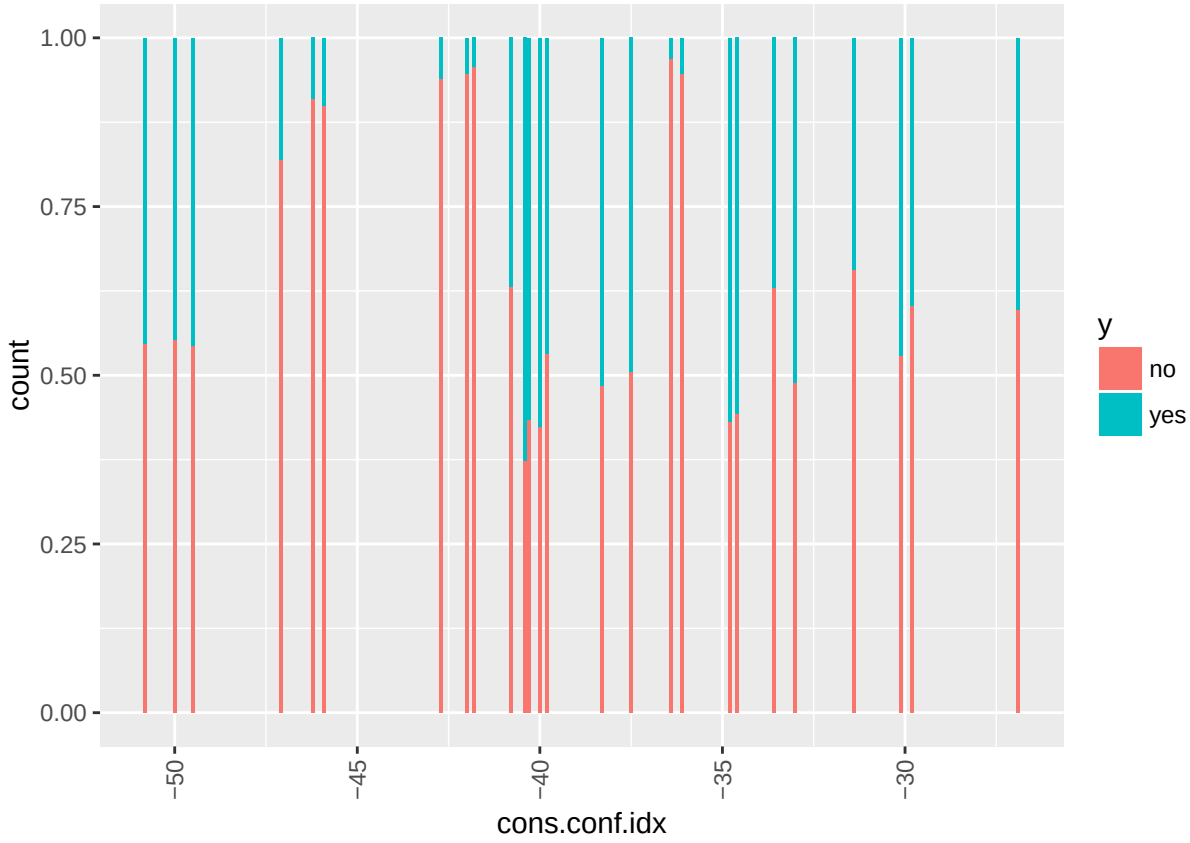
305



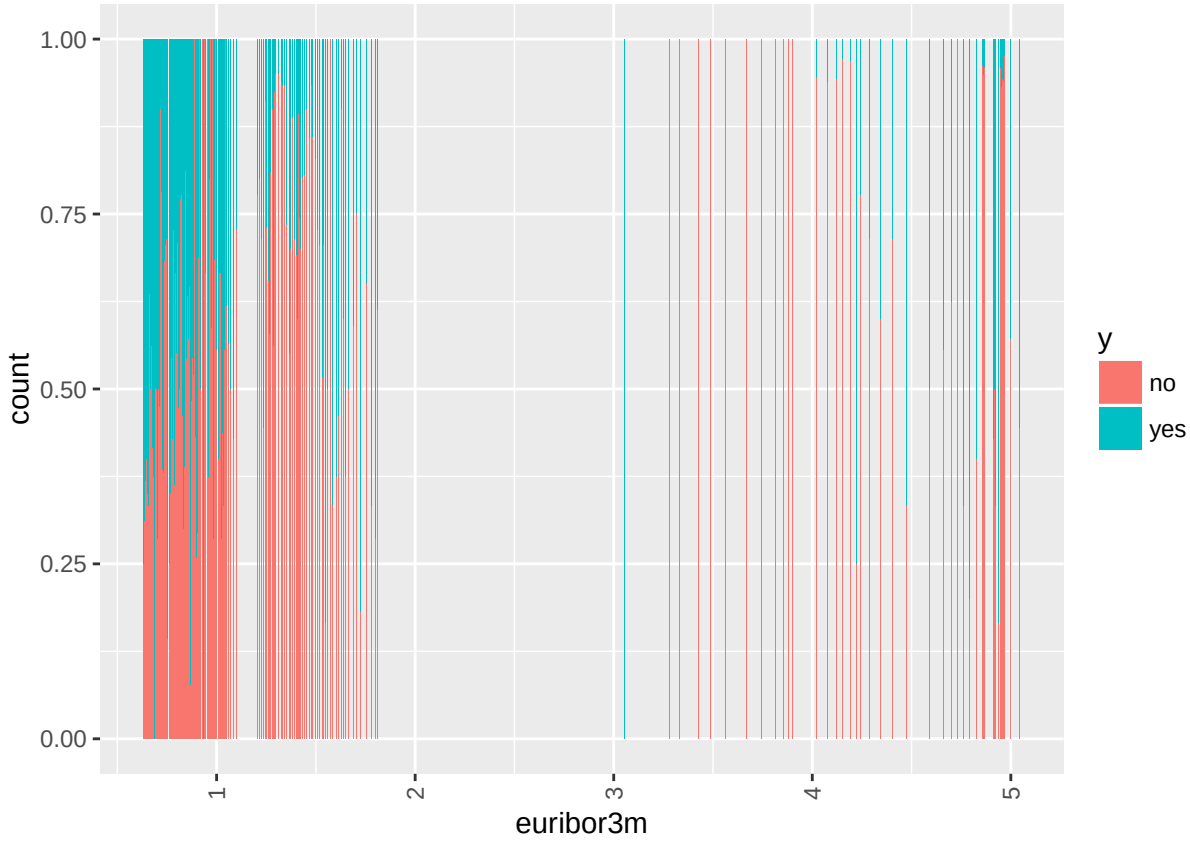
306



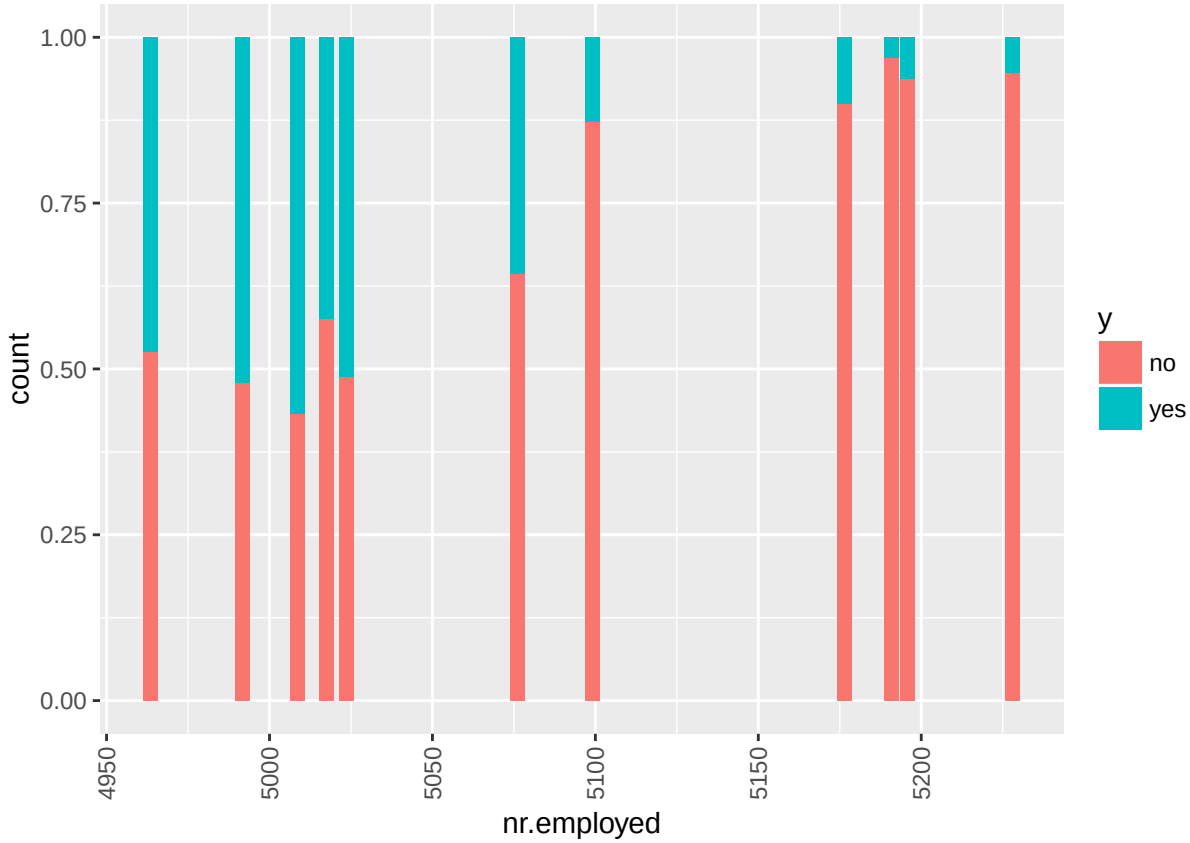
307



308



309



6.1.3 Unique Value & Missing value

We see that there are no missing values in our dataset as shown in table 2 and graph format. The unique values are given in the table

Table 4

Missing Values

	Missing Values
age	0
job	0
marital	0
education	0
default	0
housing	0

	Missing Values
loan	0
contact	0
month	0
day_of_week	0
duration	0
campaign	0
pdays	0
previous	0
poutcome	0
emp.var.rate	0
cons.price.idx	0
cons.conf.idx	0
euribor3m	0
nr.employed	0
y	0

Table 5

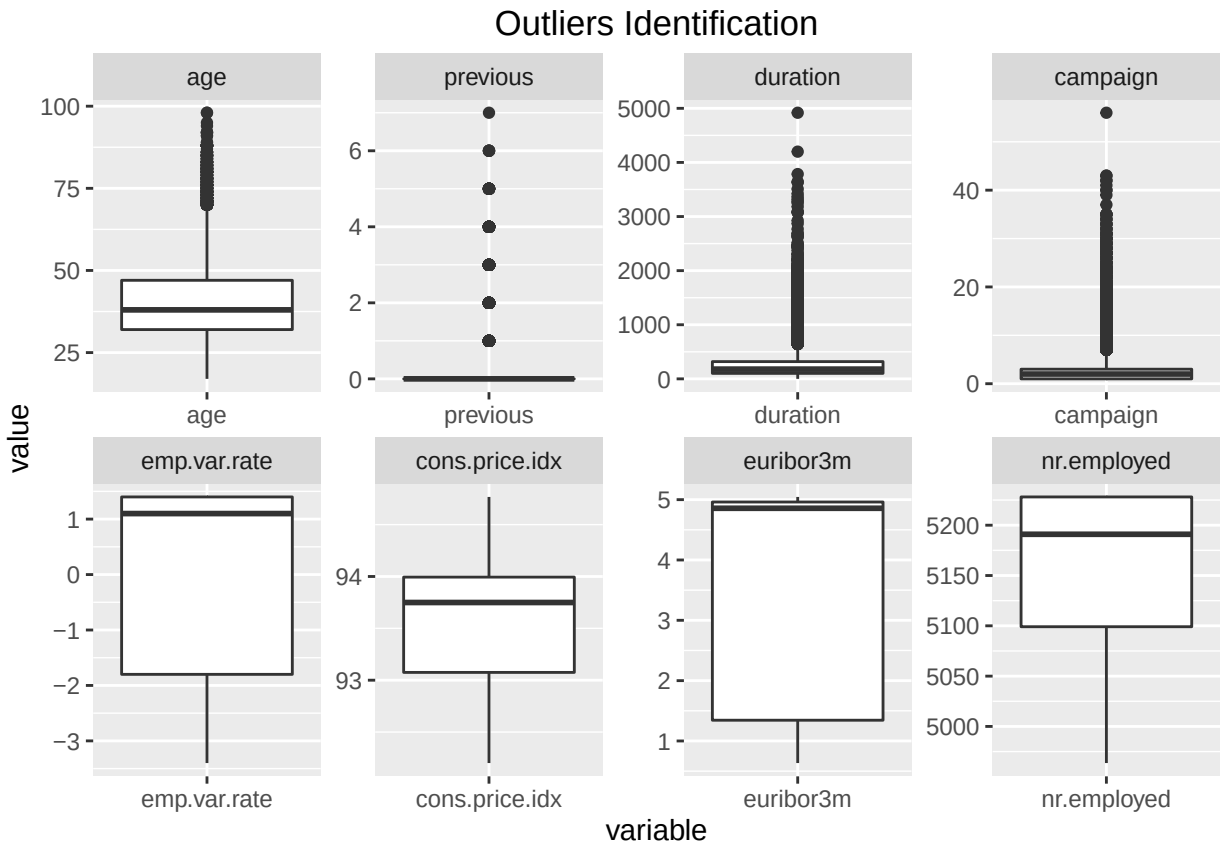
Unique Values

	Unique Values
age	78
job	12
marital	4
education	8
default	3
housing	3

	Unique Values
loan	3
contact	2
month	10
day_of_week	5
duration	1544
campaign	42
pdays	27
previous	8
poutcome	3
emp.var.rate	10
cons.price.idx	26
cons.conf.idx	26
euribor3m	316
nr.employed	11
y	2

6.1.4 Data Summary post conversion

6.1.5 Outliers Analysis



6.1.6 Analysis of link functions for given variables

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