Business Analytics - Final Project

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Contents

Overview

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.

1 Data Exploration Analysis

In section we will explore and gain some insights into the dataset by pursuing the below high level steps and inquiries:
-Variable identification
-Understanding predictor variables relationship with response variable -Missing values and Unique Values

1.1 Variable identification

First let's display and examine the data dictionary or the data columns as shown in table 1

We notice that the variables are numerical, categorical and binary. The responce 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.

1.2 Preliminary Data Analysis

1.2.1 Analysis of Predictor variable

Table 1: Variable Analysis

Variable	Data.Type	Analysis
age	Numeric	No significant trend with responses variable, better response with age grp<30 & >55
job	Catagorical	12 levels, proportion of responses from admin and blue collar job profiles are higher
marital	Catagorical	4 levels, % response from marital status from single is greater compare to other grp
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 from unknown
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 response
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 variable
previous	Numeric	previous contacts seems to have influence on the positive response of the campaign
poutcome	Catagorical	have relationship with campaign outcome, earlier success has better response to positive outc
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 to spend less that
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

1.2.2 Missing values

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

1.2.3 Proportion of Response Variables

2 Data Preparation

-Convert Binary to 0 and 1
-Create dummy variables
-Data Summary Analysis
-Correlation of Variables with y

2.1 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.

2.2 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.

2.3 Data Summary with Dummy variables

2.4 Correlation between Response and Predictor of Variables

Now we will produce the correlation table between the independent variables and the dependent variable

2.5 Outliers Handling

2.6 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:

$g(E(y)) = a + Bx_1 + B_2x_2 + B_3x_3 + ...$

where, g() is the link function, E(y) is the expectation of target variable and $B_0 + B_1x_1 + B_2x_2 + B_3x_3$ is the linear predictor (B_0, B_1, B_2, B_3 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 (p) and Probability of Failure (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).

3 Build Models

In this section, we will create 3 models. Aside from using original and transformed data, we will also be using different methods and functions such as Linear Discriminant Analysis, step function, and logit function to enhance our models.

Below is our model definition:

-Model 1- This model will be created using all the variables in train data set with logit function GLM.

-Model 2: This model step function will be used to enhance the model 1.

-Model 3- This model will be created using calssification and regression tree.

3.1 Model 1

Taking the treated data and splitting into 80/20 to train model and validate the data.

3.2 Model 2

3.3 Model 3

4 Evaluate Models

5 Select Models

6 Appendix

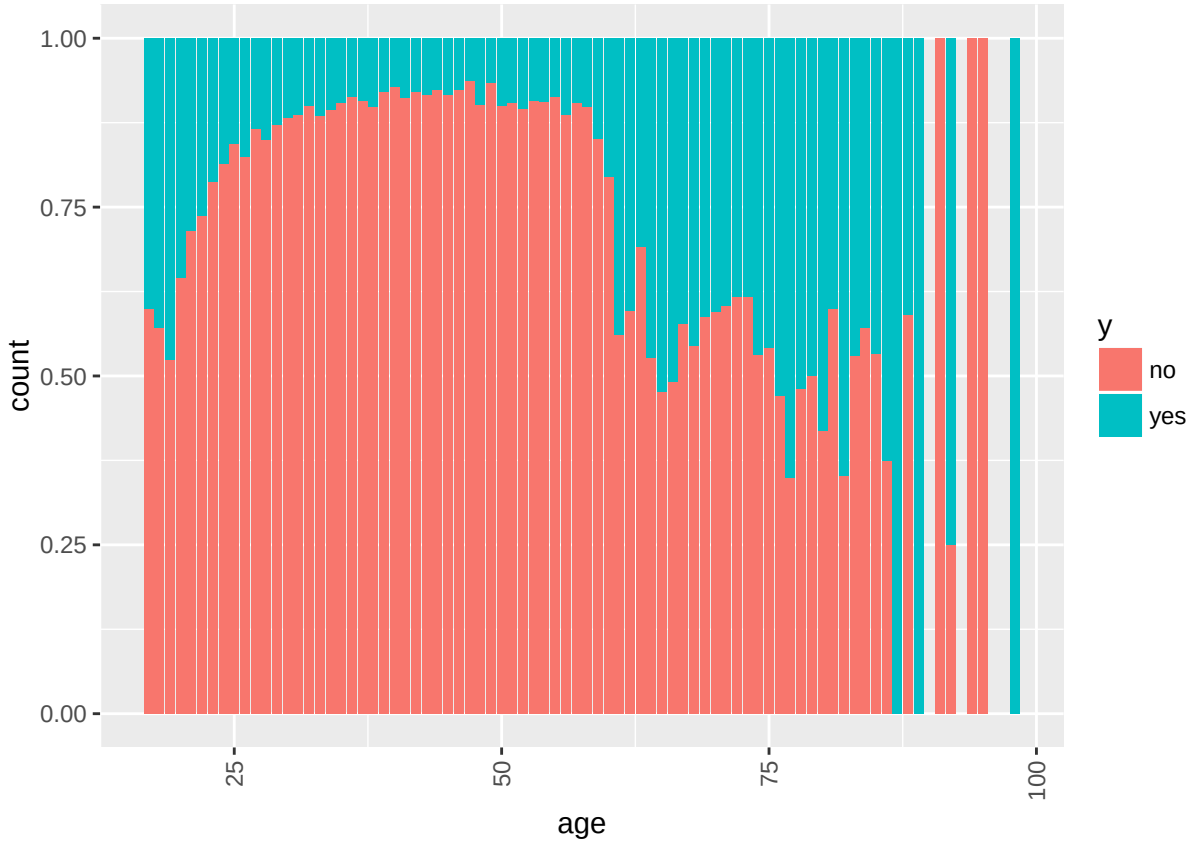
6.1 Data Analysis details

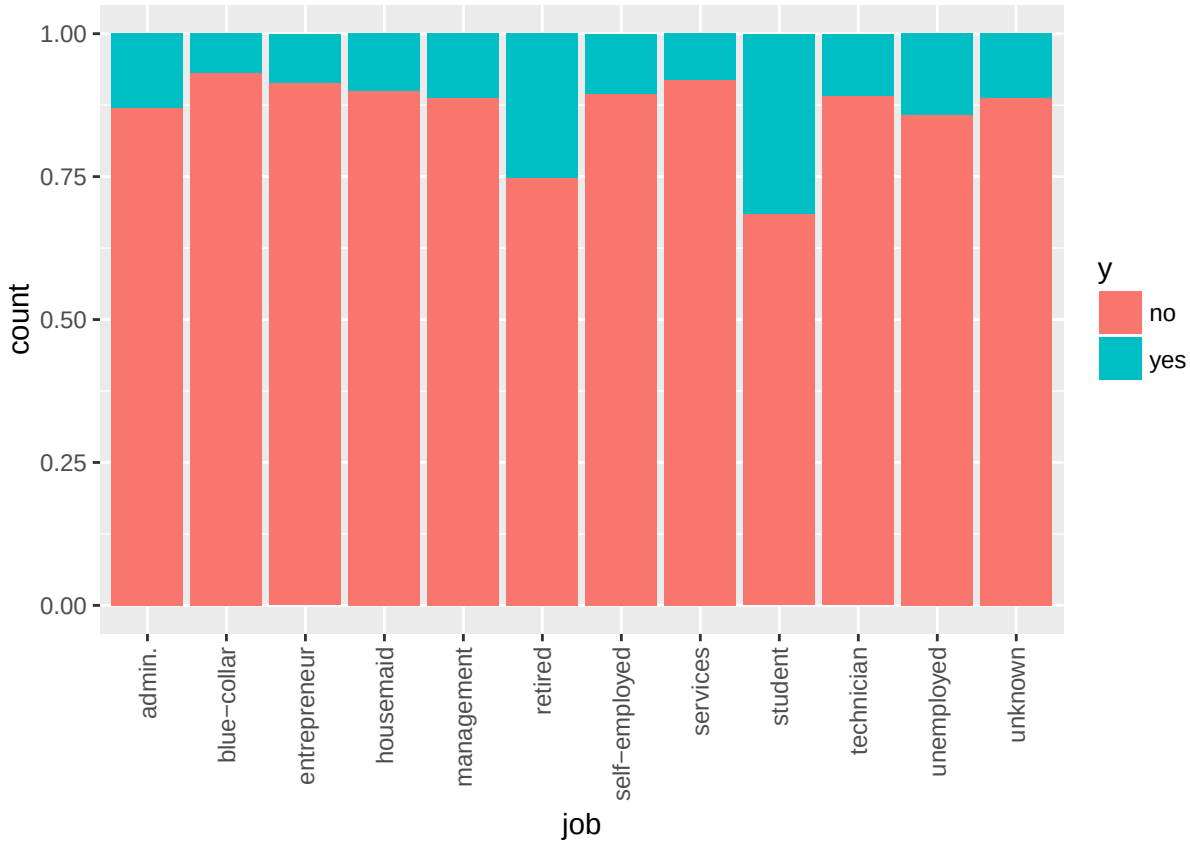
6.1.1 Variable Description

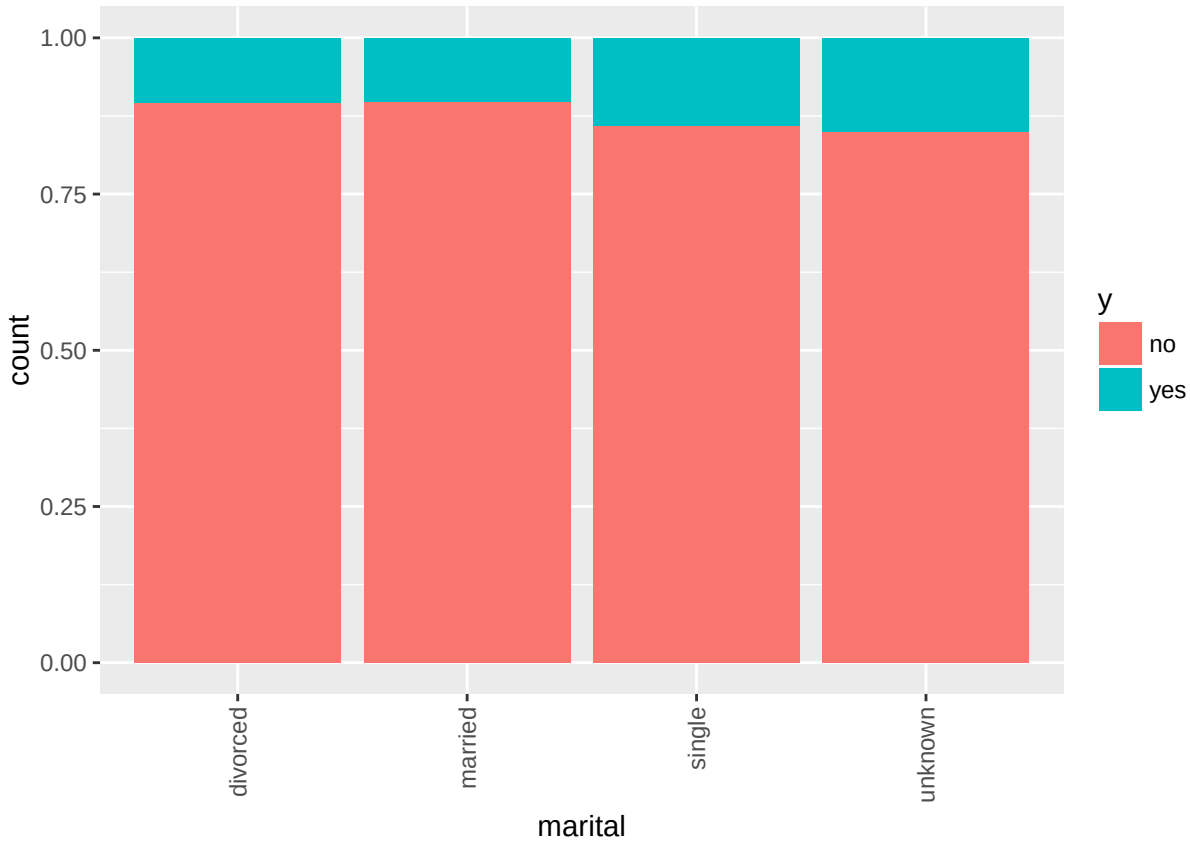
Table 2: Variable Description

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
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 number of days that passed by after the client was last contacted
previous	Numeric	Predictor	Number of contacts performed before this campaign and for this client
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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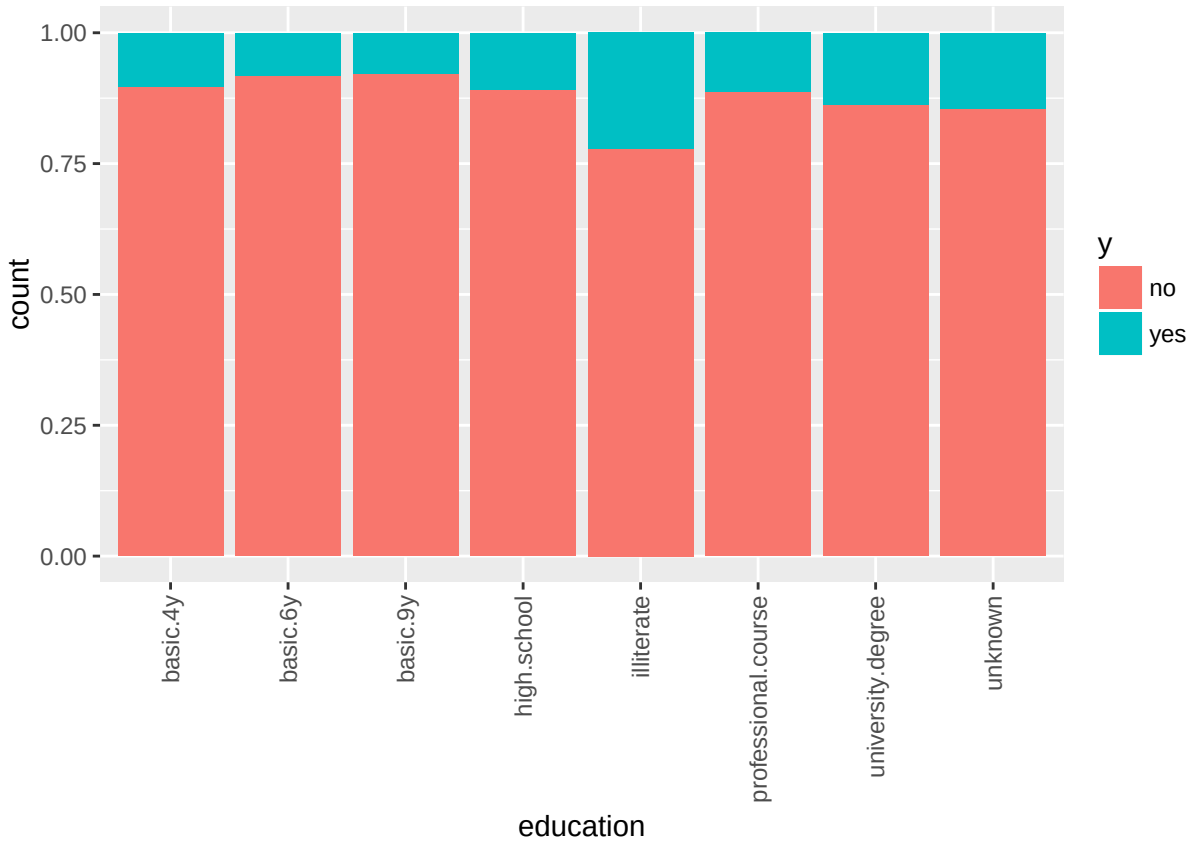
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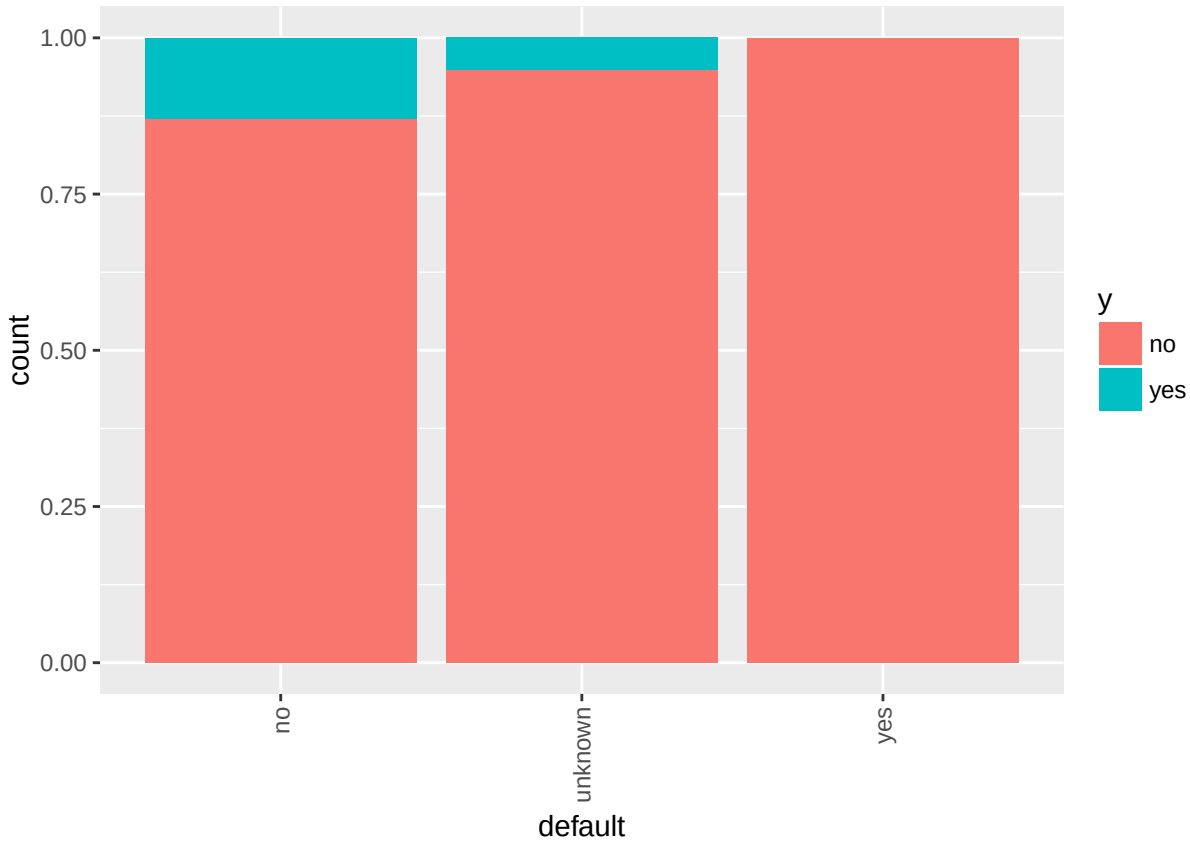
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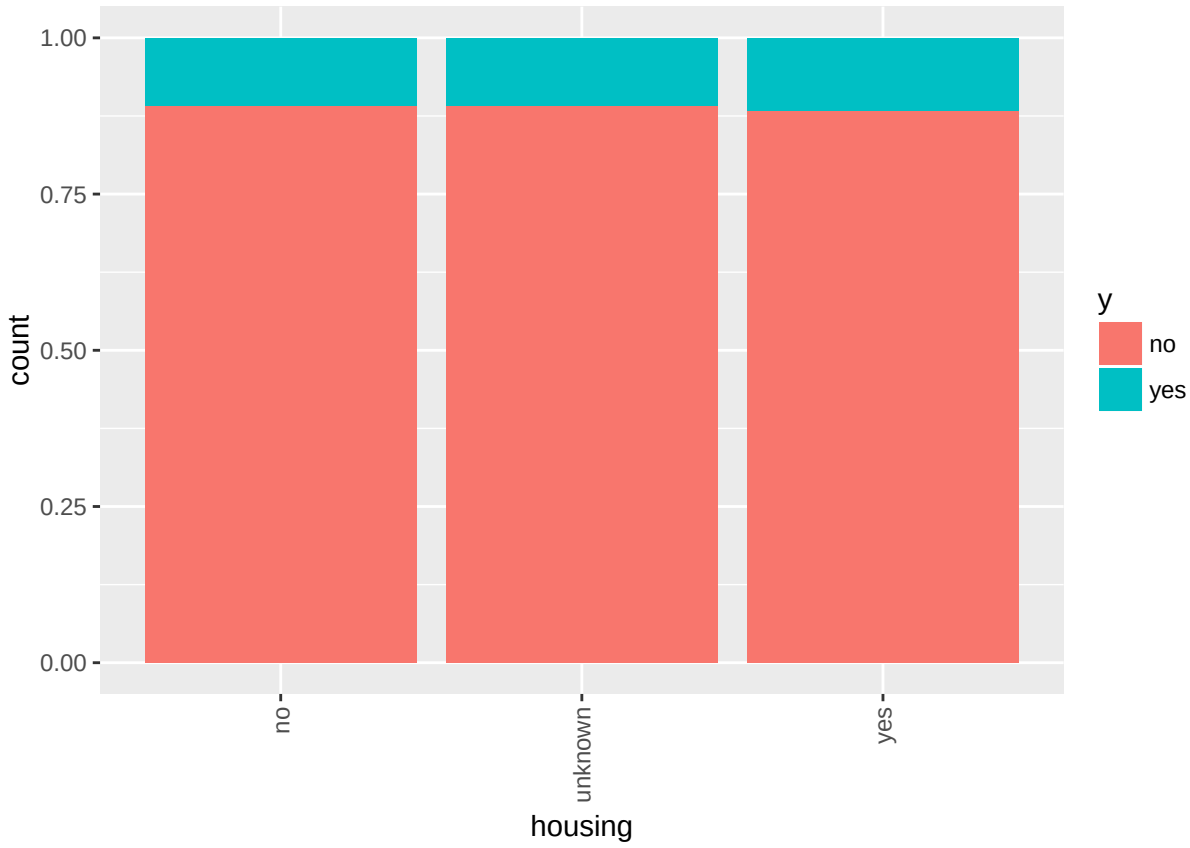
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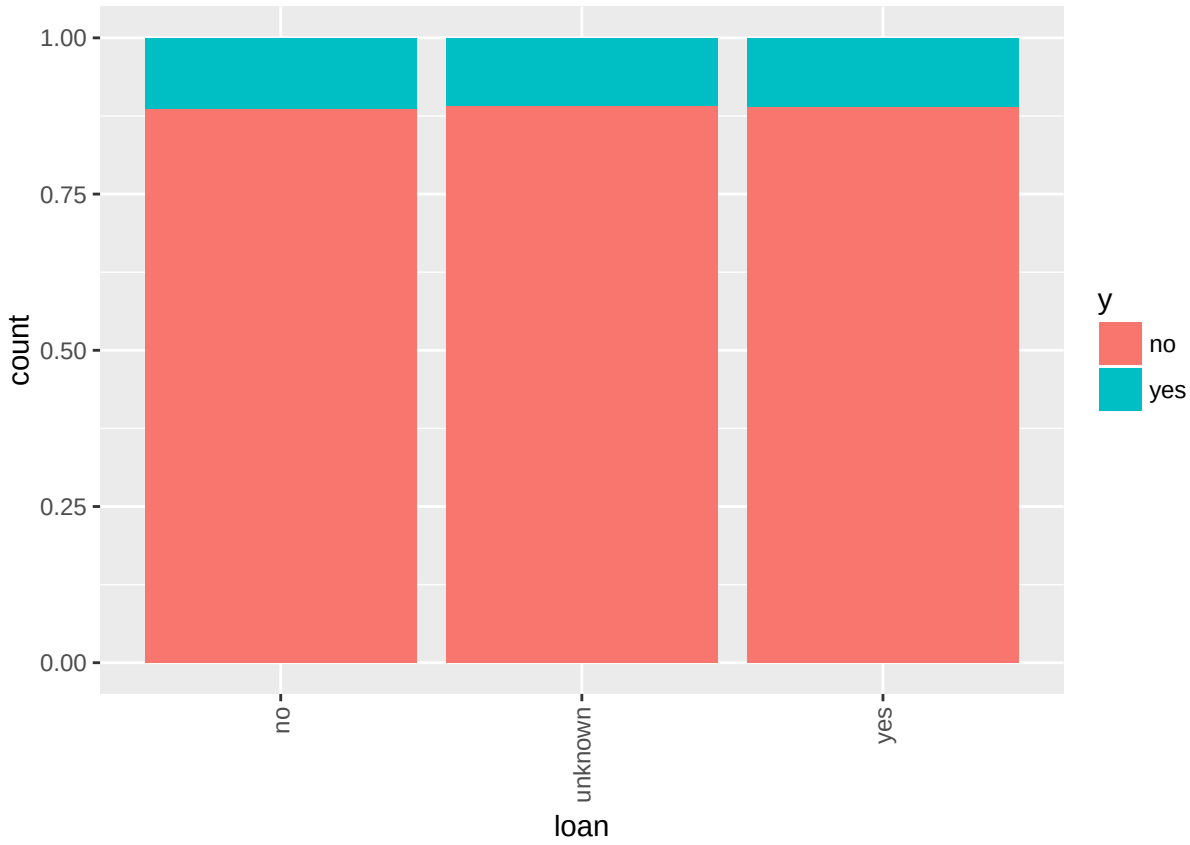
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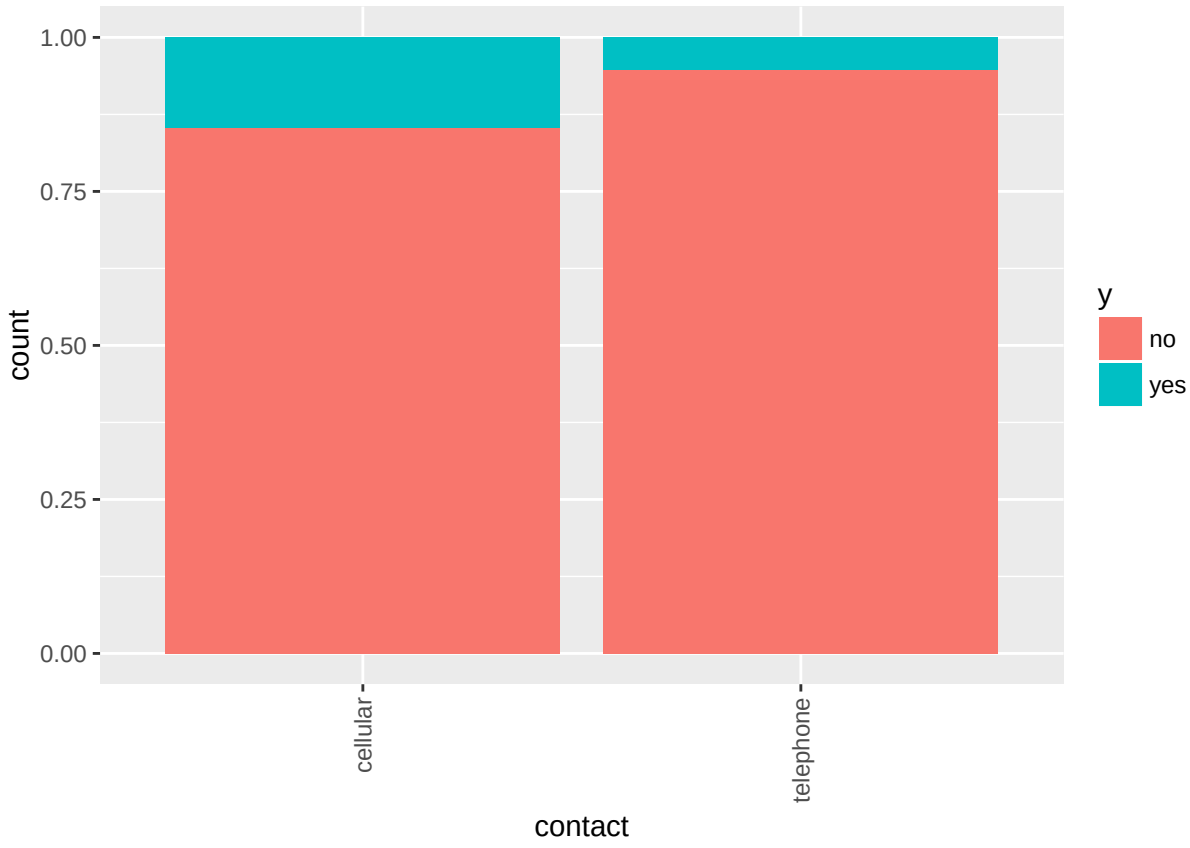
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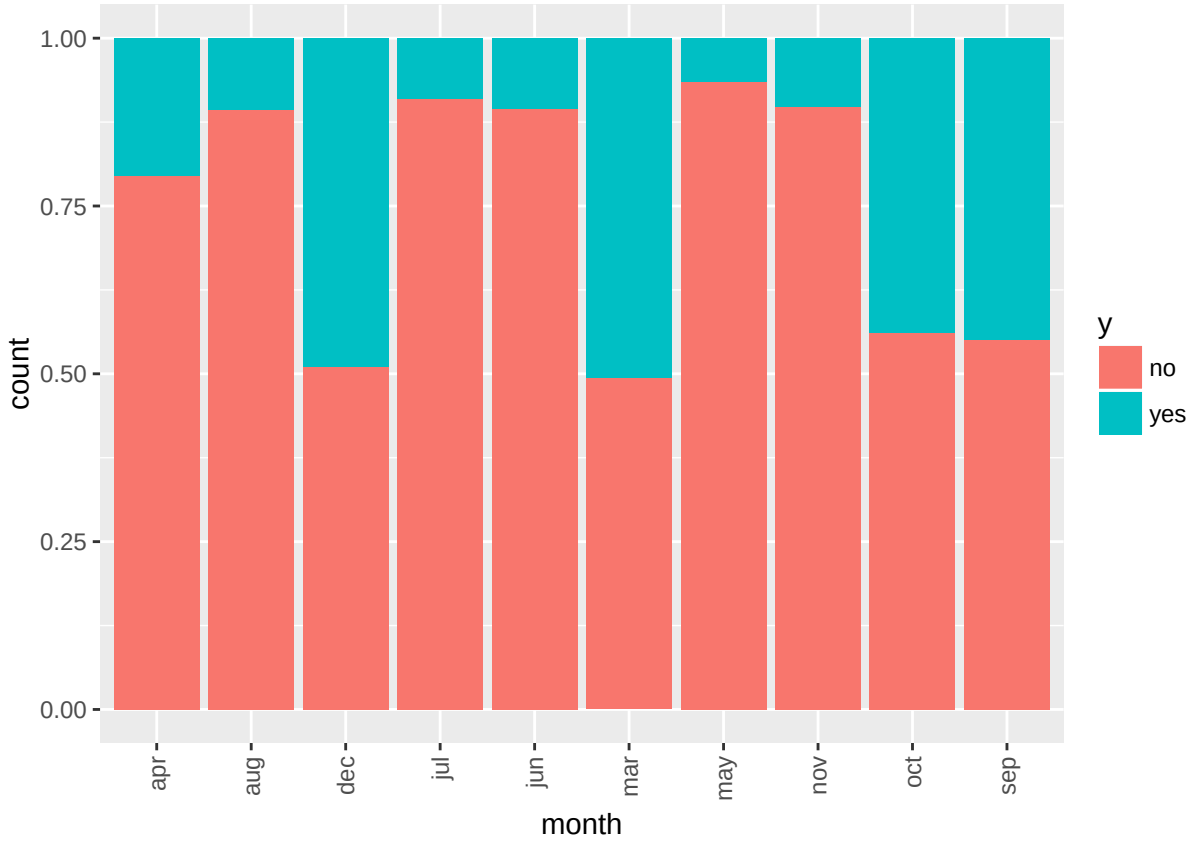
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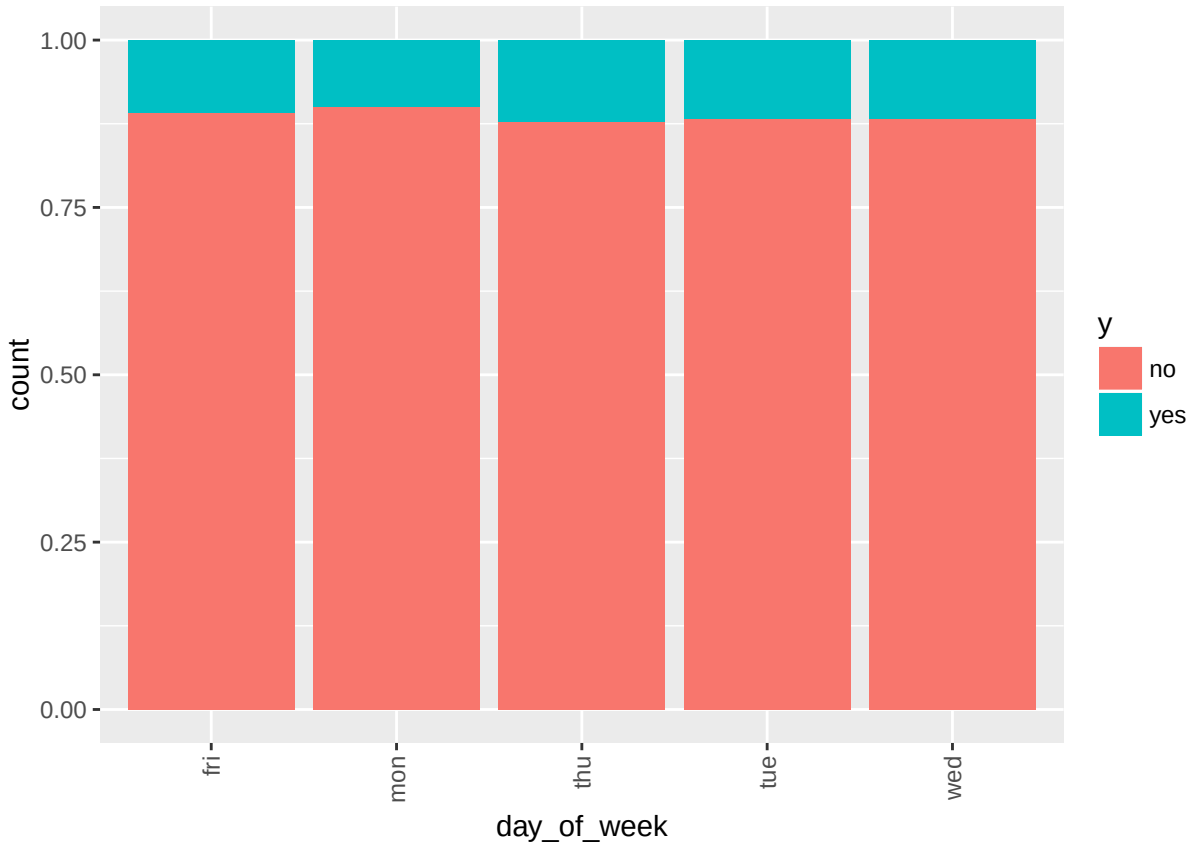
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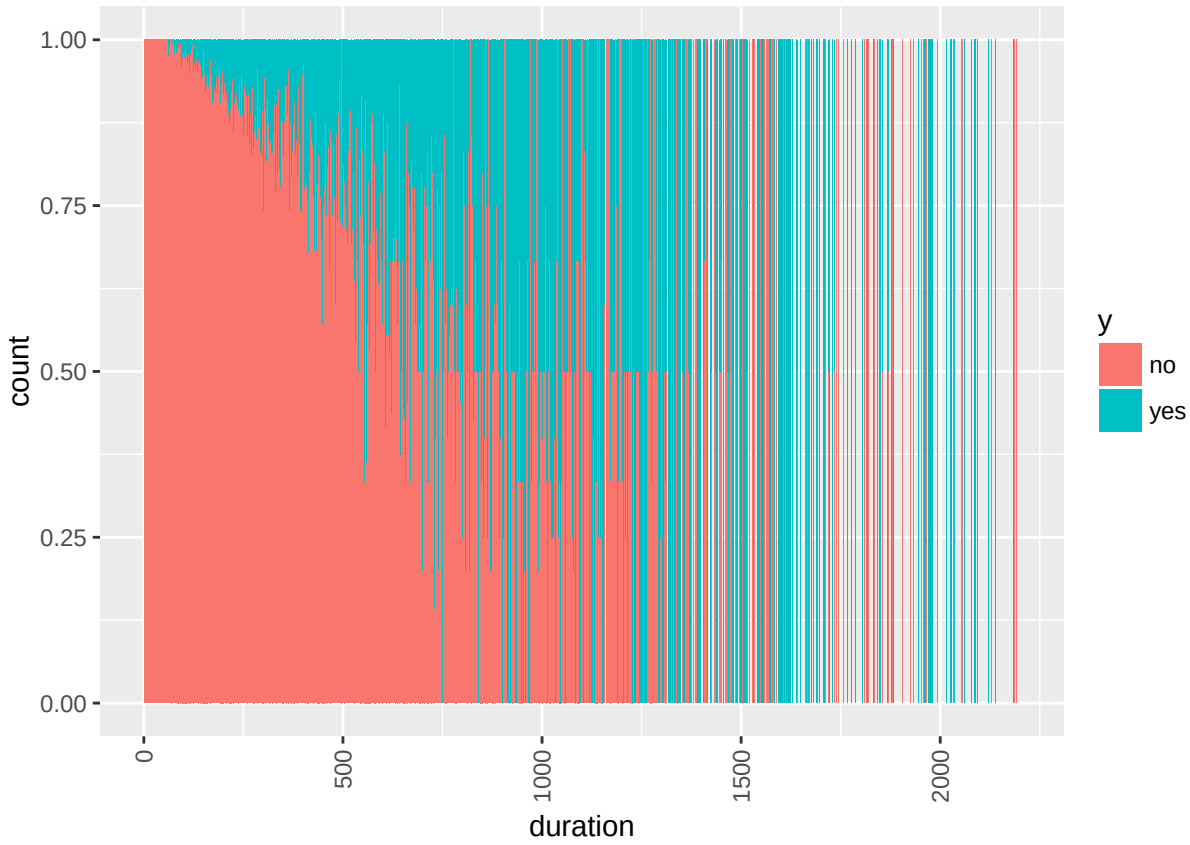
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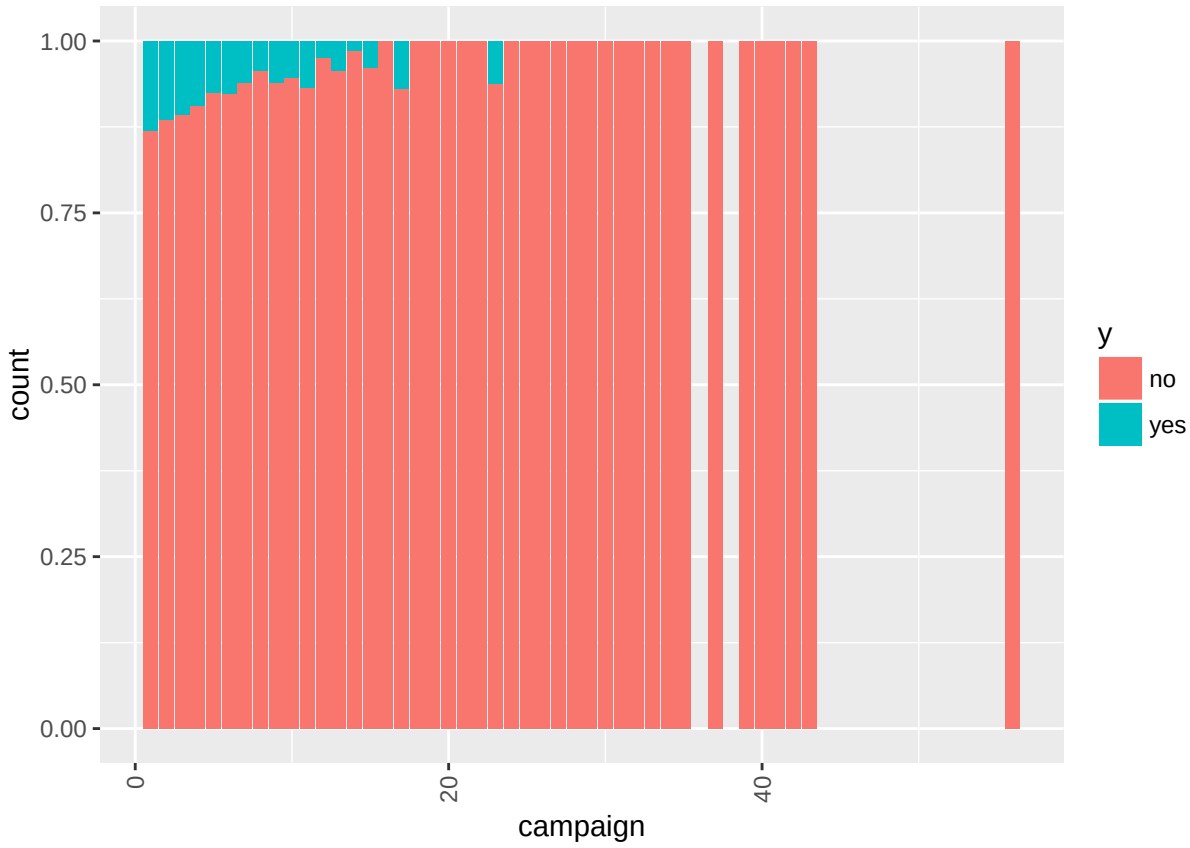
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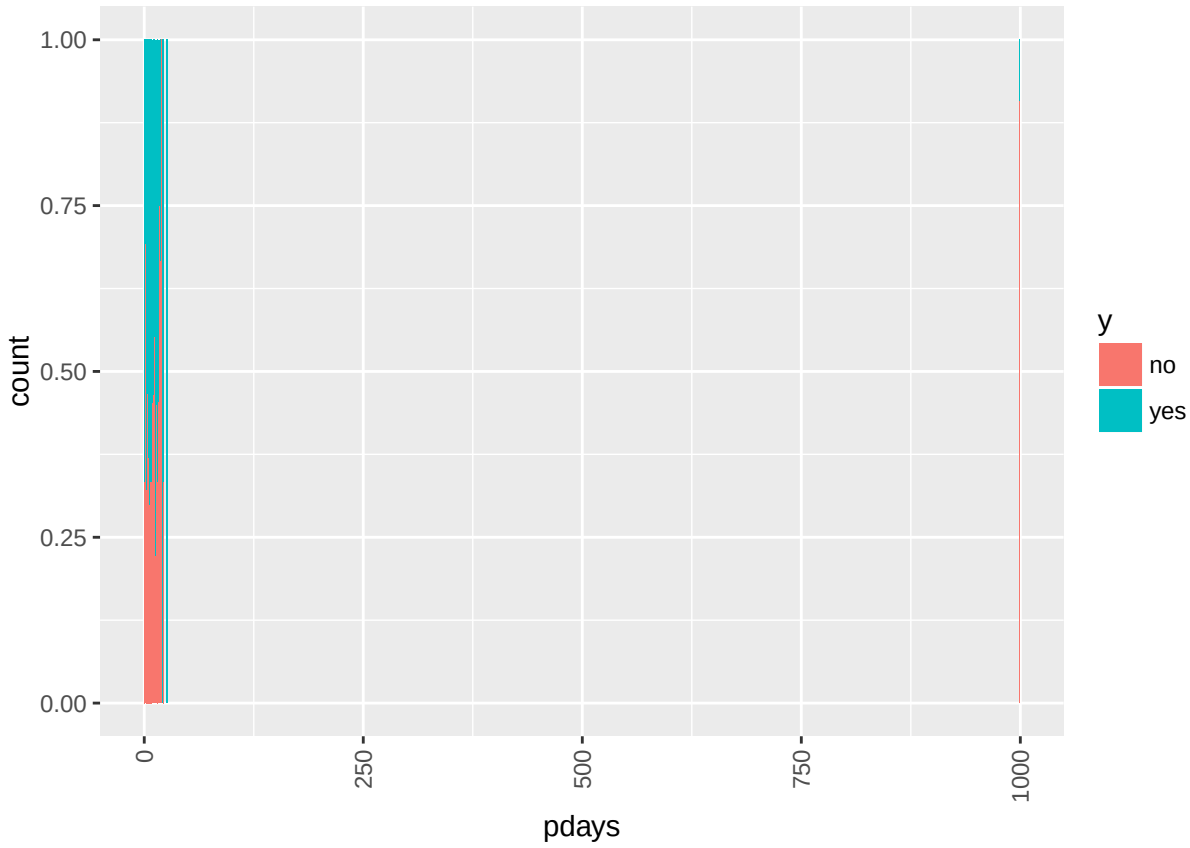
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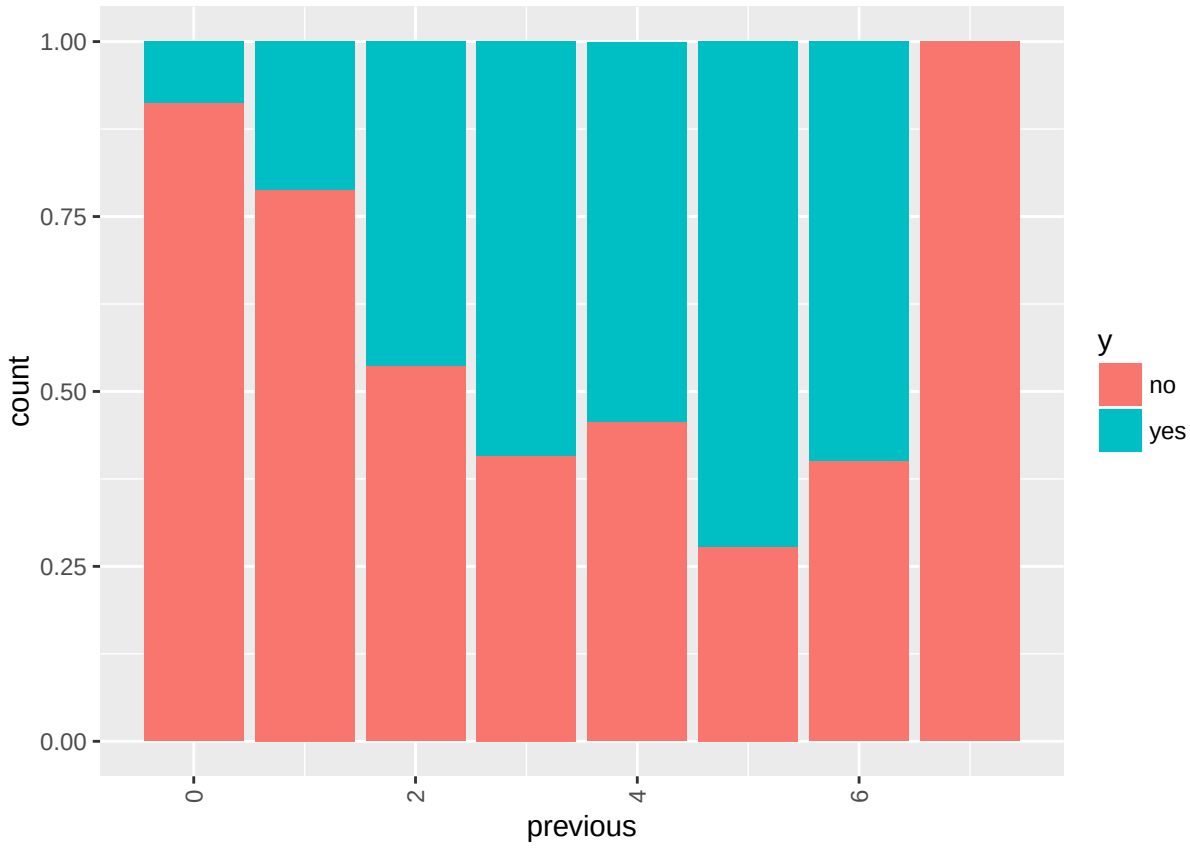
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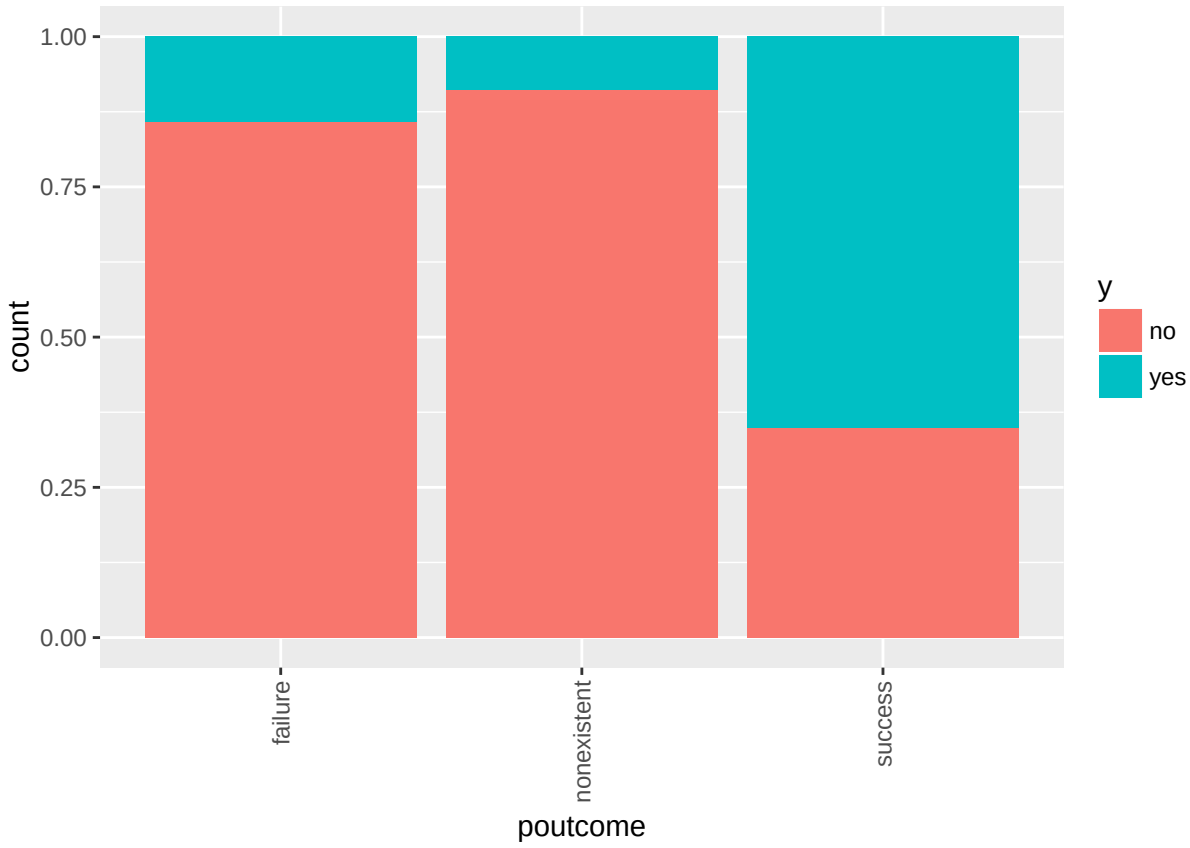
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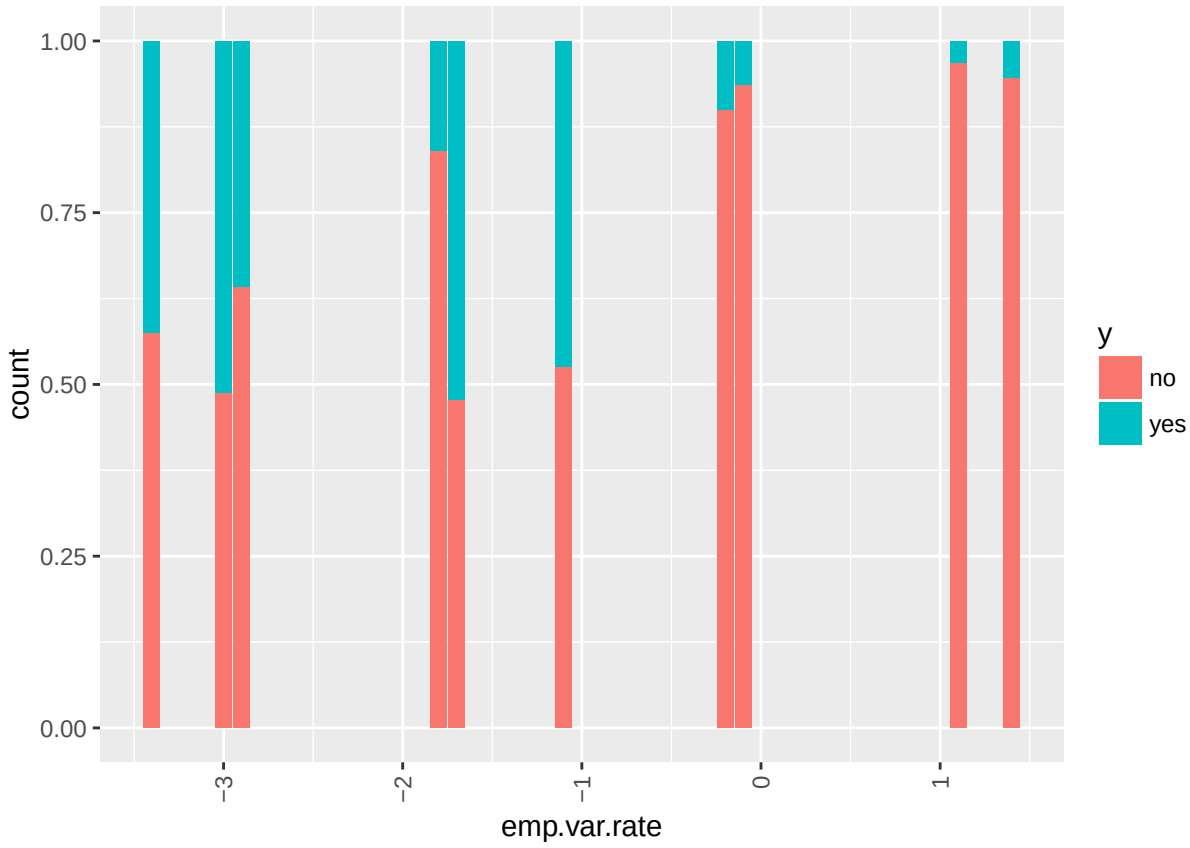
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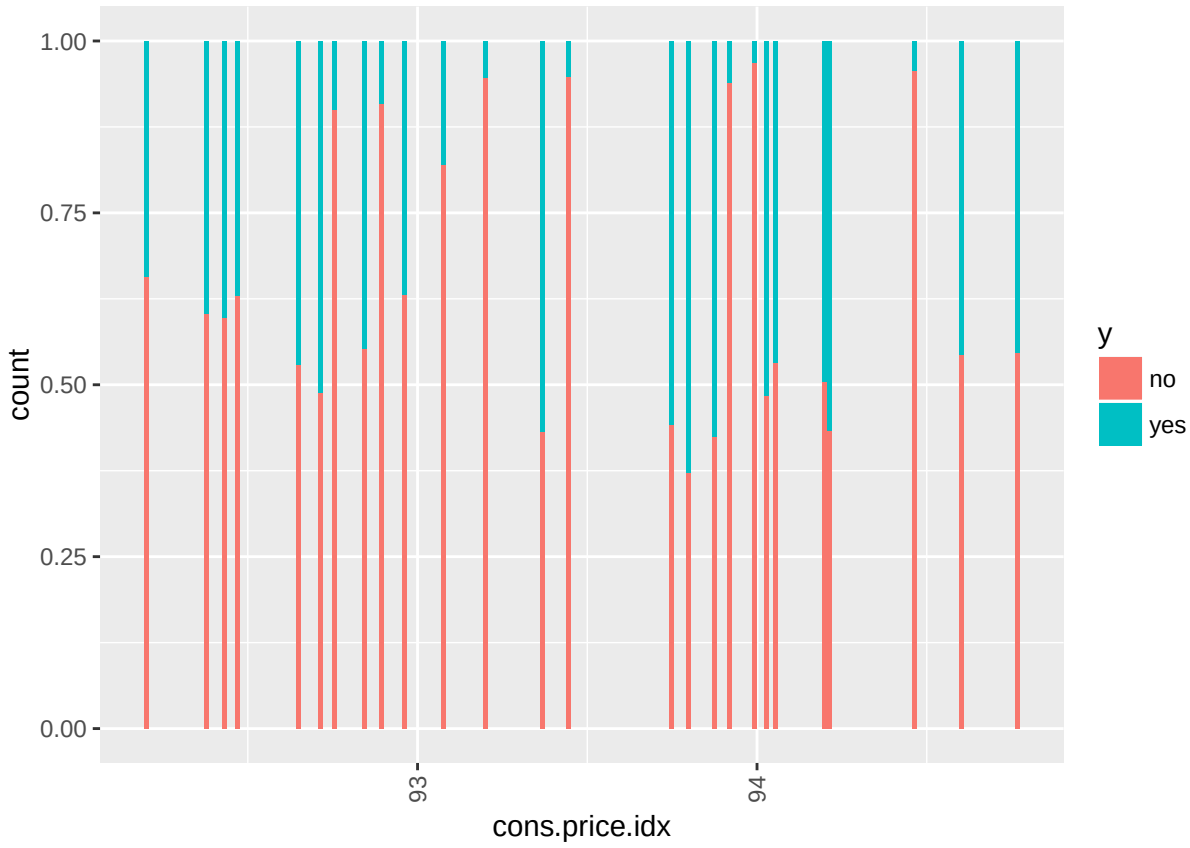
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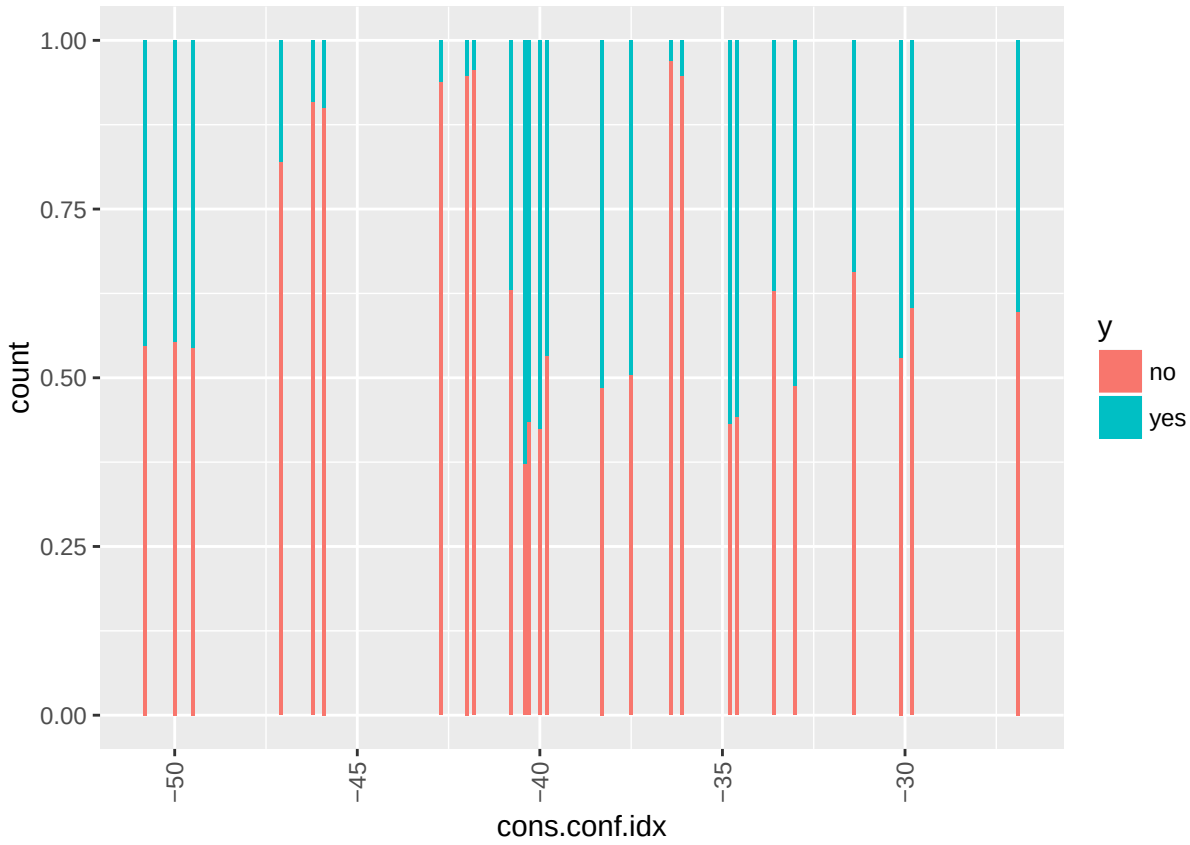
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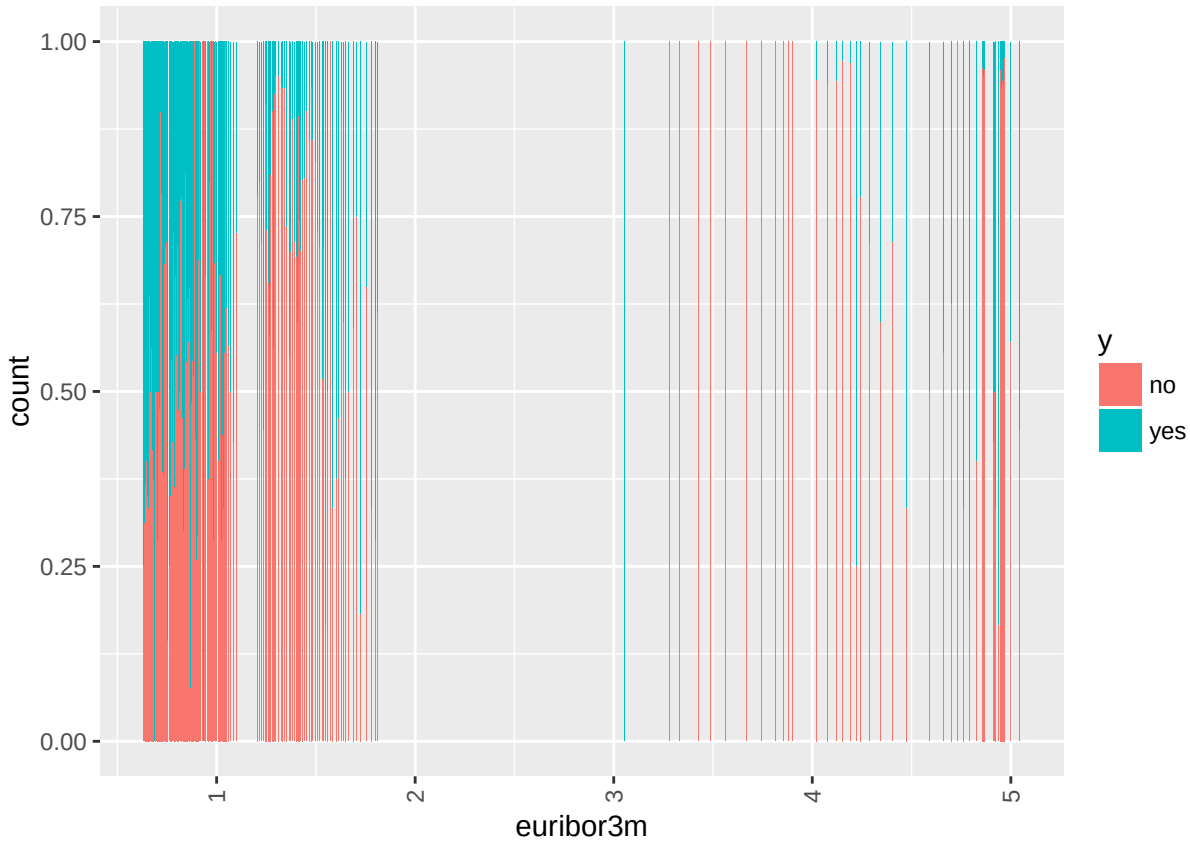
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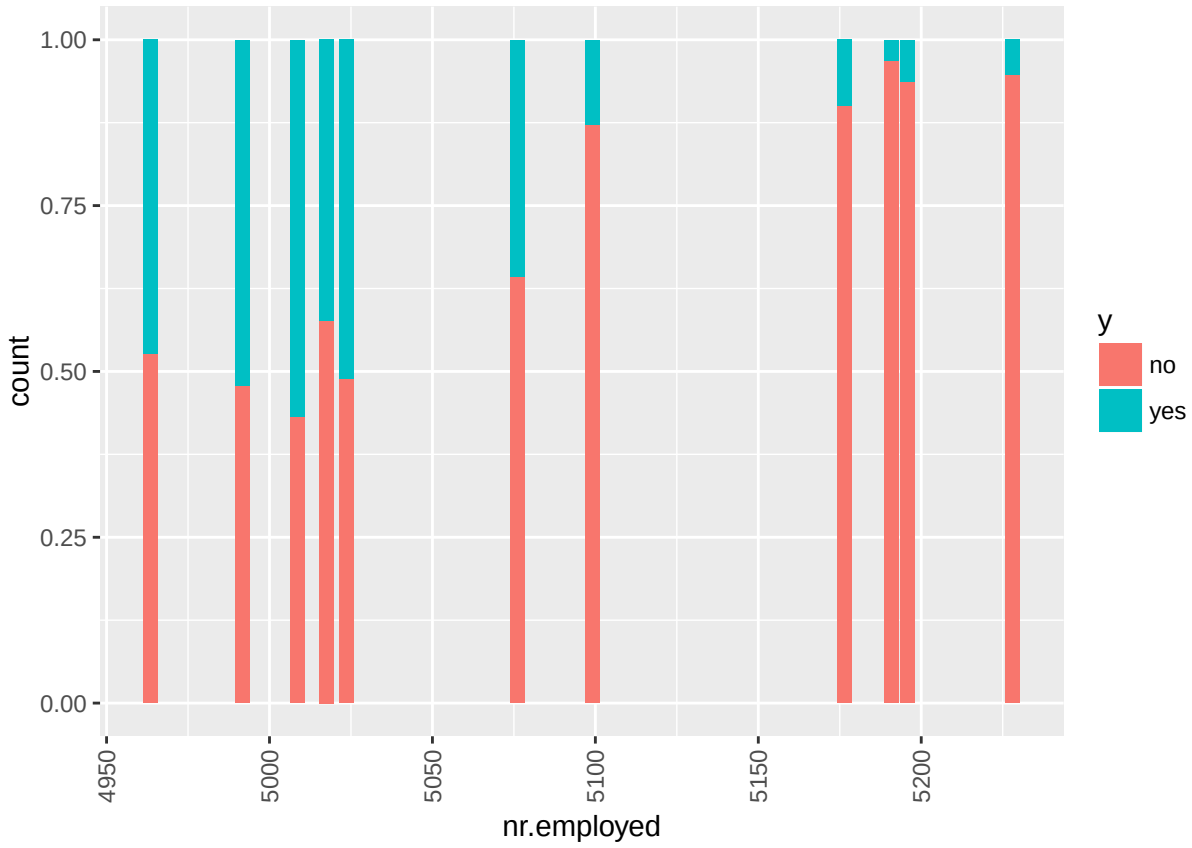


6.1.3 Unique Value & Missing value

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 3: Missing Values

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

	Missing Values
cons.conf.idx	0
euribor3m	0
nr.employed	0
y	0

Table 4: Unique Values

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

Table 5: Data Summary

	vars	n	mean	sd	median	trimmed	mad
age	1	41188	40.0240604	10.4212500	38.000	39.3033807	10.3782000
duration	2	41188	258.2850102	259.2792488	180.000	210.6102513	139.3644000
campaign	3	41188	2.5675925	2.7700135	2.000	1.9914118	1.4826000
pdays	4	41188	962.4754540	186.9109073	999.000	999.0000000	0.0000000
previous	5	41188	0.1729630	0.4949011	0.000	0.0457332	0.0000000
emp.var.rate	6	41188	0.0818855	1.5709597	1.100	0.2661204	0.4447800
cons.price.idx	7	41188	93.5756644	0.5788400	93.749	93.5807666	0.5633880
cons.conf.idx	8	41188	-40.5026003	4.6281979	-41.800	-40.6015356	6.5234400
euribor3m	9	41188	3.6212908	1.7344474	4.857	3.8055852	0.1601208
nr.employed	10	41188	5167.0359109	72.2515277	5191.000	5178.4253338	55.0044600
y	11	41188	0.1126542	0.3161734	0.000	0.0158412	0.0000000
job_housemaid	12	41188	0.0257357	0.1583475	0.000	0.0000000	0.0000000
job_services	13	41188	0.0963630	0.2950920	0.000	0.0000000	0.0000000

	vars	n	mean	sd	median	trimmed	mad
job_admin.	14	41188	0.2530349	0.4347560	0.000	0.1913086	0.0000000
job_blue-collar	15	41188	0.2246771	0.4173746	0.000	0.1558631	0.0000000
job_technician	16	41188	0.1637127	0.3700192	0.000	0.0796613	0.0000000
job_retired	17	41188	0.0417597	0.2000421	0.000	0.0000000	0.0000000
job_management	18	41188	0.0709916	0.2568138	0.000	0.0000000	0.0000000
job_unemployed	19	41188	0.0246188	0.1549623	0.000	0.0000000	0.0000000
job_self-employed	20	41188	0.0345003	0.1825127	0.000	0.0000000	0.0000000
job_unknown	21	41188	0.0080120	0.0891518	0.000	0.0000000	0.0000000
job_entrepreneur	22	41188	0.0353501	0.1846654	0.000	0.0000000	0.0000000
job_student	23	41188	0.0212441	0.1441986	0.000	0.0000000	0.0000000
marital_married	24	41188	0.6052248	0.4888083	1.000	0.6315246	0.0000000
marital_single	25	41188	0.2808585	0.4494240	0.000	0.2260864	0.0000000
marital_divorced	26	41188	0.1119744	0.3153387	0.000	0.0149915	0.0000000
marital_unknown	27	41188	0.0019423	0.0440294	0.000	0.0000000	0.0000000
education_illiterate	28	41188	0.0004370	0.0209007	0.000	0.0000000	0.0000000
education_unknown	29	41188	0.0420268	0.2006528	0.000	0.0000000	0.0000000
education_primary	30	41188	0.1570360	0.3638392	0.000	0.0713159	0.0000000
education_secondary	31	41188	0.3777799	0.4848381	0.000	0.3472323	0.0000000
education_tertiary	32	41188	0.4227202	0.4939977	0.000	0.4034050	0.0000000
default_no	33	41188	0.7912013	0.4064552	1.000	0.8639840	0.0000000
default_unknown	34	41188	0.2087258	0.4064030	0.000	0.1359250	0.0000000
default_yes	35	41188	0.0000728	0.0085342	0.000	0.0000000	0.0000000
housing_no	36	41188	0.4521220	0.4977085	0.000	0.4401554	0.0000000
housing_yes	37	41188	0.5238419	0.4994373	1.000	0.5298009	0.0000000
housing_unknown	38	41188	0.0240361	0.1531632	0.000	0.0000000	0.0000000
loan_no	39	41188	0.8242692	0.3805956	1.000	0.9053168	0.0000000
loan_yes	40	41188	0.1516947	0.3587290	0.000	0.0646395	0.0000000
loan_unknown	41	41188	0.0240361	0.1531632	0.000	0.0000000	0.0000000
contact_telephone	42	41188	0.3652520	0.4815066	0.000	0.3315732	0.0000000
contact_cellular	43	41188	0.6347480	0.4815066	1.000	0.6684268	0.0000000
month_may	44	41188	0.3342964	0.4717496	0.000	0.2928806	0.0000000
month_jun	45	41188	0.1291153	0.3353316	0.000	0.0364166	0.0000000
month_jul	46	41188	0.1741769	0.3792662	0.000	0.0927410	0.0000000
month_aug	47	41188	0.1499951	0.3570710	0.000	0.0625152	0.0000000
month_oct	48	41188	0.0174323	0.1308770	0.000	0.0000000	0.0000000
month_nov	49	41188	0.0995678	0.2994265	0.000	0.0000000	0.0000000
month_dec	50	41188	0.0044188	0.0663276	0.000	0.0000000	0.0000000
month_mar	51	41188	0.0132563	0.1143717	0.000	0.0000000	0.0000000
month_apr	52	41188	0.0639021	0.2445814	0.000	0.0000000	0.0000000
month_sep	53	41188	0.0138390	0.1168238	0.000	0.0000000	0.0000000
day_of_week_mon	54	41188	0.2067107	0.4049511	0.000	0.1334062	0.0000000
day_of_week_tue	55	41188	0.1964164	0.3972919	0.000	0.1205390	0.0000000
day_of_week_wed	56	41188	0.1974847	0.3981059	0.000	0.1218742	0.0000000
day_of_week_thu	57	41188	0.2093571	0.4068547	0.000	0.1367140	0.0000000
day_of_week_fri	58	41188	0.1900311	0.3923302	0.000	0.1125577	0.0000000
previous_contact	59	41188	0.0367826	0.1882298	0.000	0.0000000	0.0000000
poutcome_nonexistent	60	41188	0.8634311	0.3433958	1.000	0.9542668	0.0000000
poutcome_failure	61	41188	0.1032340	0.3042679	0.000	0.0040665	0.0000000
poutcome_success	62	41188	0.0333350	0.1795119	0.000	0.0000000	0.0000000

Table 6: Data Summary (Cont)

	min	max	range	skew	kurtosis	se
age	17.000	98.000	81.000	0.7846397	0.7908857	0.0513493
duration	0.000	4918.000	4918.000	3.2629036	20.2442057	1.2775632
campaign	1.000	56.000	55.000	4.7621598	36.9732194	0.0136489
pdays	0.000	999.000	999.000	-4.9218314	22.2253936	0.9209781
previous	0.000	7.000	7.000	3.8317631	20.1051076	0.0024386
emp.var.rate	-3.400	1.400	4.800	-0.7240428	-1.0627423	0.0077407
cons.price.idx	92.201	94.767	2.566	-0.2308708	-0.8299589	0.0028522
cons.conf.idx	-50.800	-26.900	23.900	0.3031578	-0.3587887	0.0228048
euribor3m	0.634	5.045	4.411	-0.7091363	-1.4068549	0.0085463
nr.employed	4963.600	5228.100	264.500	-1.0441863	-0.0040511	0.3560096
y	0.000	1.000	1.000	2.4501517	4.0033404	0.0015579
job_housemaid	0.000	1.000	1.000	5.9900255	33.8812283	0.0007802
job_services	0.000	1.000	1.000	2.7356021	5.4836522	0.0014540
job_admin.	0.000	1.000	1.000	1.1360815	-0.7093361	0.0021422
job_blue-collar	0.000	1.000	1.000	1.3192765	-0.2595158	0.0020566
job_technician	0.000	1.000	1.000	1.8176306	1.3038128	0.0018232
job_retired	0.000	1.000	1.000	4.5813276	18.9890235	0.0009857
job_management	0.000	1.000	1.000	3.3409260	9.1620092	0.0012654
job_unemployed	0.000	1.000	1.000	6.1352936	35.6426931	0.0007636
job_self-employed	0.000	1.000	1.000	5.1008881	24.0196428	0.0008993
job_unknown	0.000	1.000	1.000	11.0368168	119.8142342	0.0004393
job_entrepreneur	0.000	1.000	1.000	5.0322224	23.3238288	0.0009099
job_student	0.000	1.000	1.000	6.6400673	42.0915155	0.0007105
marital_married	0.000	1.000	1.000	-0.4305257	-1.8146917	0.0024085
marital_single	0.000	1.000	1.000	0.9751869	-1.0490361	0.0022145
marital_divorced	0.000	1.000	1.000	2.4609486	4.0563667	0.0015538
marital_unknown	0.000	1.000	1.000	22.6233213	509.8270434	0.0002169
education_illiterate	0.000	1.000	1.000	47.8022616	2283.1116468	0.0001030
education_unknown	0.000	1.000	1.000	4.5647225	18.8371487	0.0009887
education_primary	0.000	1.000	1.000	1.8852047	1.5540345	0.0017928
education_secondary	0.000	1.000	1.000	0.5041563	-1.7458688	0.0023890
education_tertiary	0.000	1.000	1.000	0.3128675	-1.9021601	0.0024341
default_no	0.000	1.000	1.000	-1.4328481	0.0530549	0.0020028
default_unknown	0.000	1.000	1.000	1.4333905	0.0546097	0.0020025
default_yes	0.000	1.000	1.000	117.1551691	13723.6668447	0.0000421
housing_no	0.000	1.000	1.000	0.1923892	-1.9630341	0.0024524
housing_yes	0.000	1.000	1.000	-0.0954727	-1.9909333	0.0024609
housing_unknown	0.000	1.000	1.000	6.2149702	36.6267442	0.0007547
loan_no	0.000	1.000	1.000	-1.7039679	0.9035286	0.0018753
loan_yes	0.000	1.000	1.000	1.9418382	1.7707787	0.0017676
loan_unknown	0.000	1.000	1.000	6.2149702	36.6267442	0.0007547
contact_telephone	0.000	1.000	1.000	0.5596796	-1.6867997	0.0023726
contact_cellular	0.000	1.000	1.000	-0.5596796	-1.6867997	0.0023726
month_may	0.000	1.000	1.000	0.7024895	-1.5065451	0.0023245
month_jun	0.000	1.000	1.000	2.2119941	2.8929884	0.0016523
month_jul	0.000	1.000	1.000	1.7181345	0.9520092	0.0018688
month_aug	0.000	1.000	1.000	1.9603741	1.8431112	0.0017594
month_oct	0.000	1.000	1.000	7.3741903	52.3799548	0.0006449
month_nov	0.000	1.000	1.000	2.6745954	5.1535859	0.0014754
month_dec	0.000	1.000	1.000	14.9430876	221.3012387	0.0003268

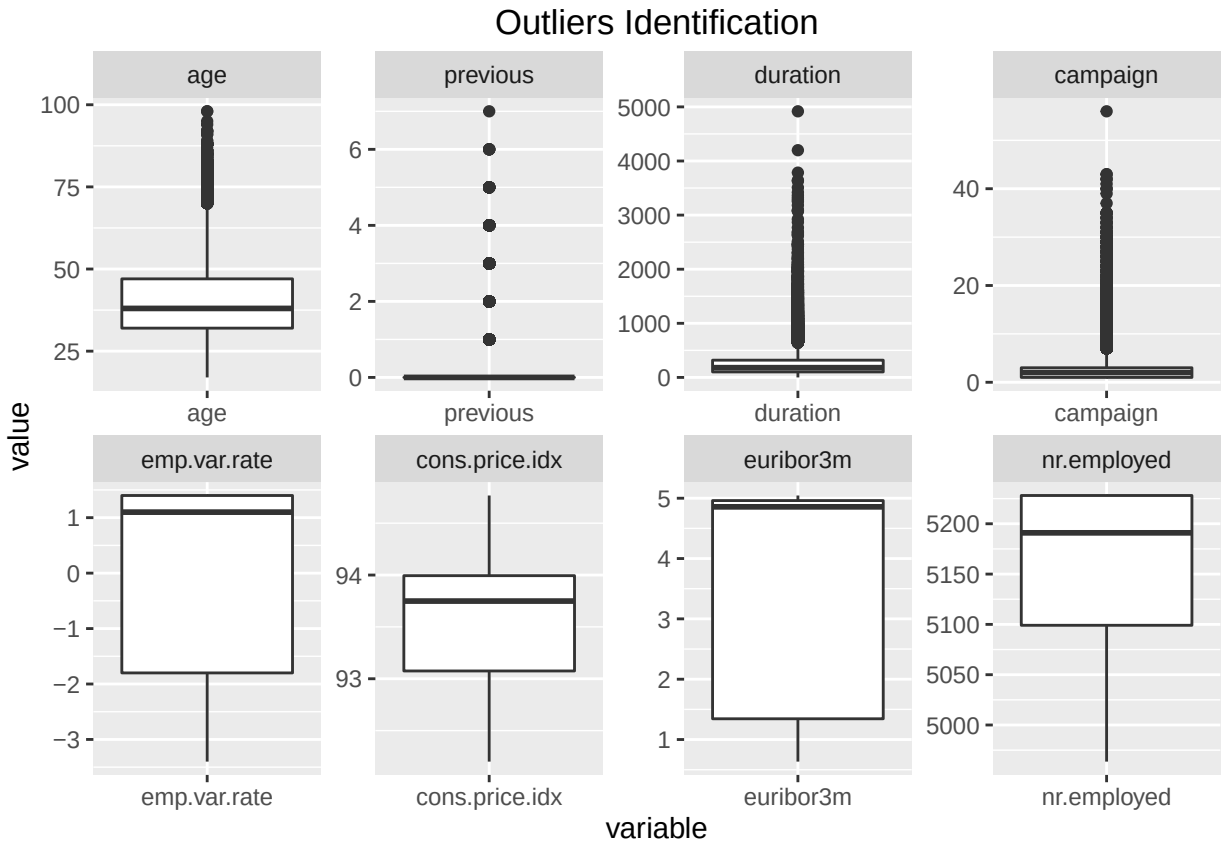
	min	max	range	skew	kurtosis	se
month_mar	0.000	1.000	1.000	8.5114073	70.4457653	0.0005636
month_apr	0.000	1.000	1.000	3.5659885	10.7165344	0.0012051
month_sep	0.000	1.000	1.000	8.3227782	67.2702700	0.0005756
day_of_week_mon	0.000	1.000	1.000	1.4484821	0.0981028	0.0019953
day_of_week_tue	0.000	1.000	1.000	1.5282275	0.3354874	0.0019576
day_of_week_wed	0.000	1.000	1.000	1.5197359	0.3096048	0.0019616
day_of_week_thu	0.000	1.000	1.000	1.4286962	0.0411737	0.0020047
day_of_week_fri	0.000	1.000	1.000	1.5801046	0.4967426	0.0019332
previous_contact	0.000	1.000	1.000	4.9217092	22.2237610	0.0009275
poutcome_nonexistent	0.000	1.000	1.000	-2.1166376	2.4802150	0.0016920
poutcome_failure	0.000	1.000	1.000	2.6079414	4.8014749	0.0014992
poutcome_success	0.000	1.000	1.000	5.1991402	25.0316666	0.0008845

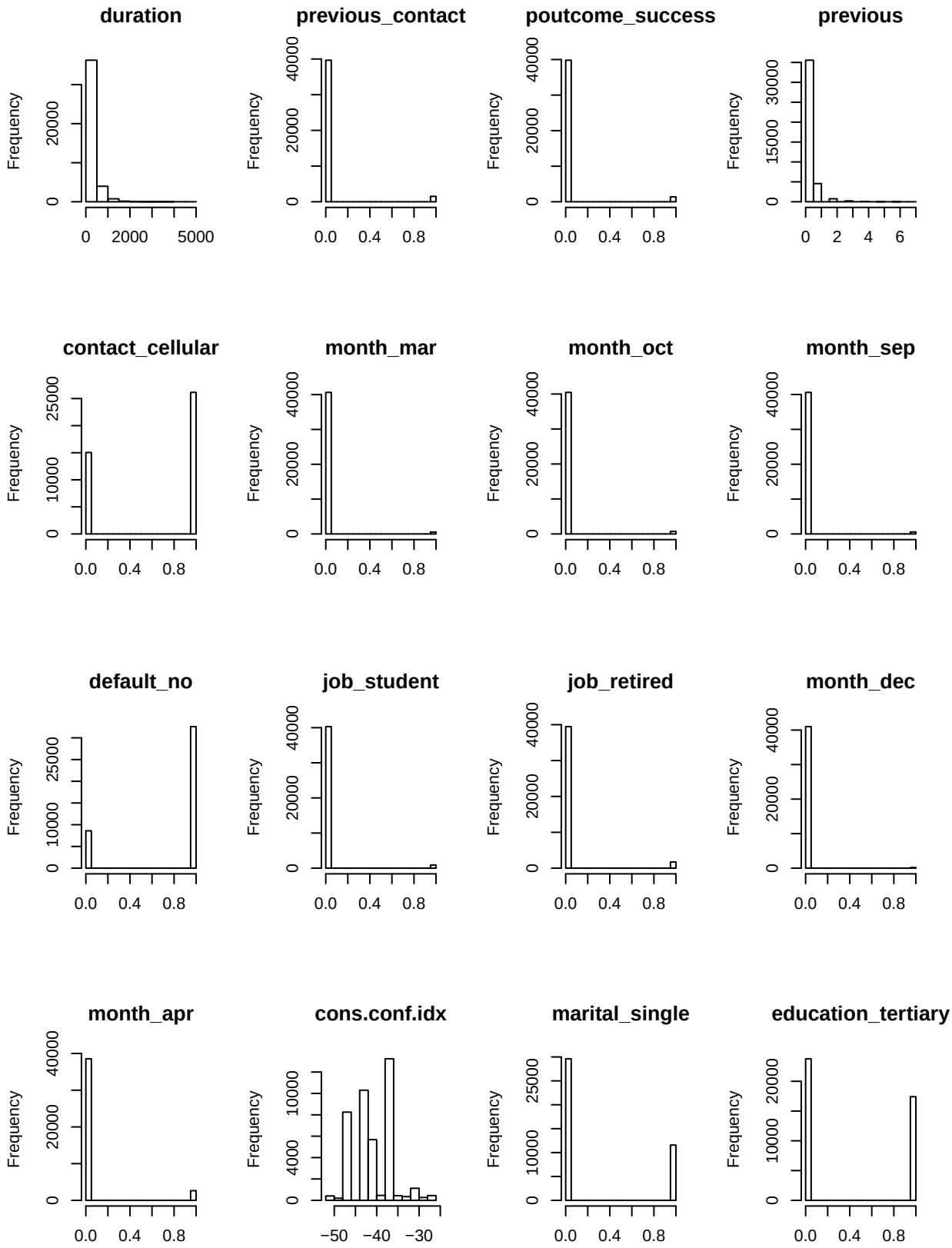
Table 7: Variable Correlation

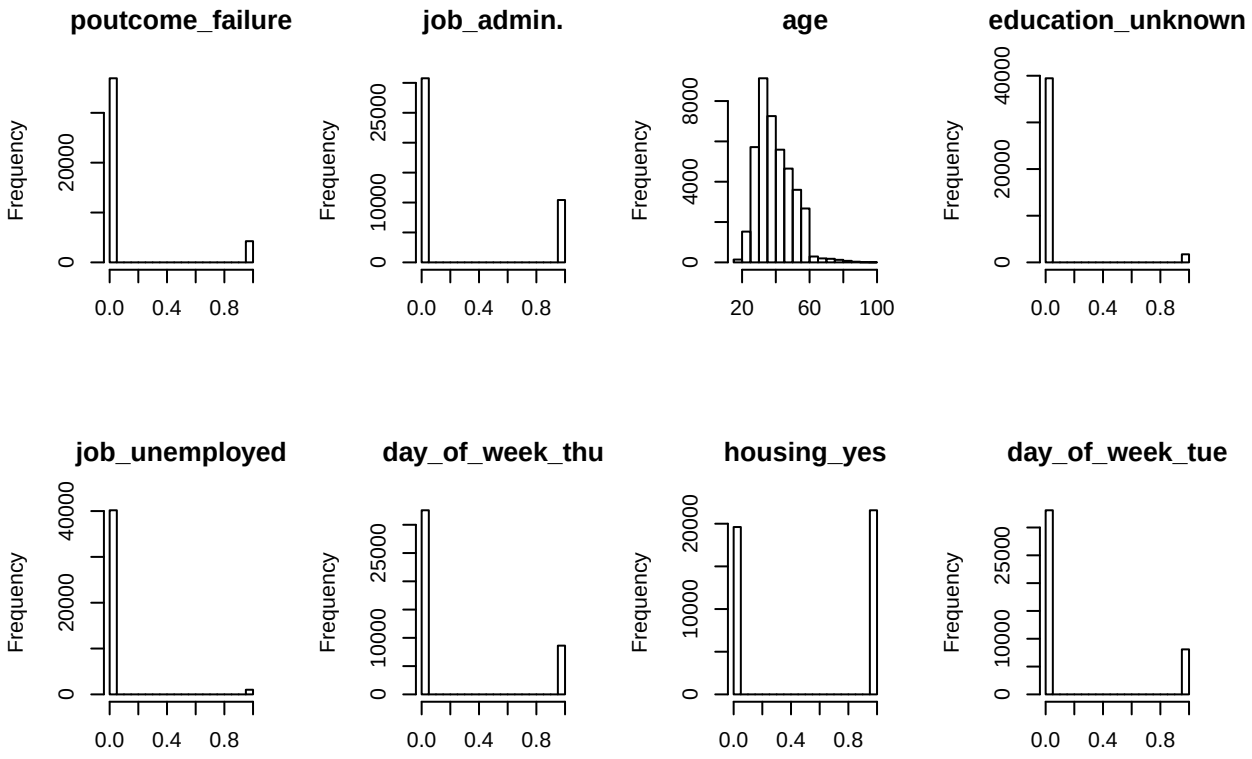
y	1.0000000
duration	0.4052738
previous_contact	0.3248767
poutcome_success	0.3162694
previous	0.2301810
contact_cellular	0.1447731
month_mar	0.1440140
month_oct	0.1373659
month_sep	0.1260674
default_no	0.0993445
job_student	0.0939550
job_retired	0.0922208
month_dec	0.0793034
month_apr	0.0761364
cons.conf.idx	0.0548779
marital_single	0.0541335
education_tertiary	0.0471911
poutcome_failure	0.0317987
job_admin.	0.0314260
age	0.0303988
education_unknown	0.0214301
job_unemployed	0.0147519
day_of_week_thu	0.0138884
housing_yes	0.0117429
day_of_week_tue	0.0080461
education_illiterate	0.0072462
day_of_week_wed	0.0063020
marital_unknown	0.0052108
loan_no	0.0051231
job_unknown	-0.0001515
job_management	-0.0004189
housing_unknown	-0.0022700
loan_unknown	-0.0022700
default_yes	-0.0030410
loan_yes	-0.0044661
job_self-employed	-0.0046625

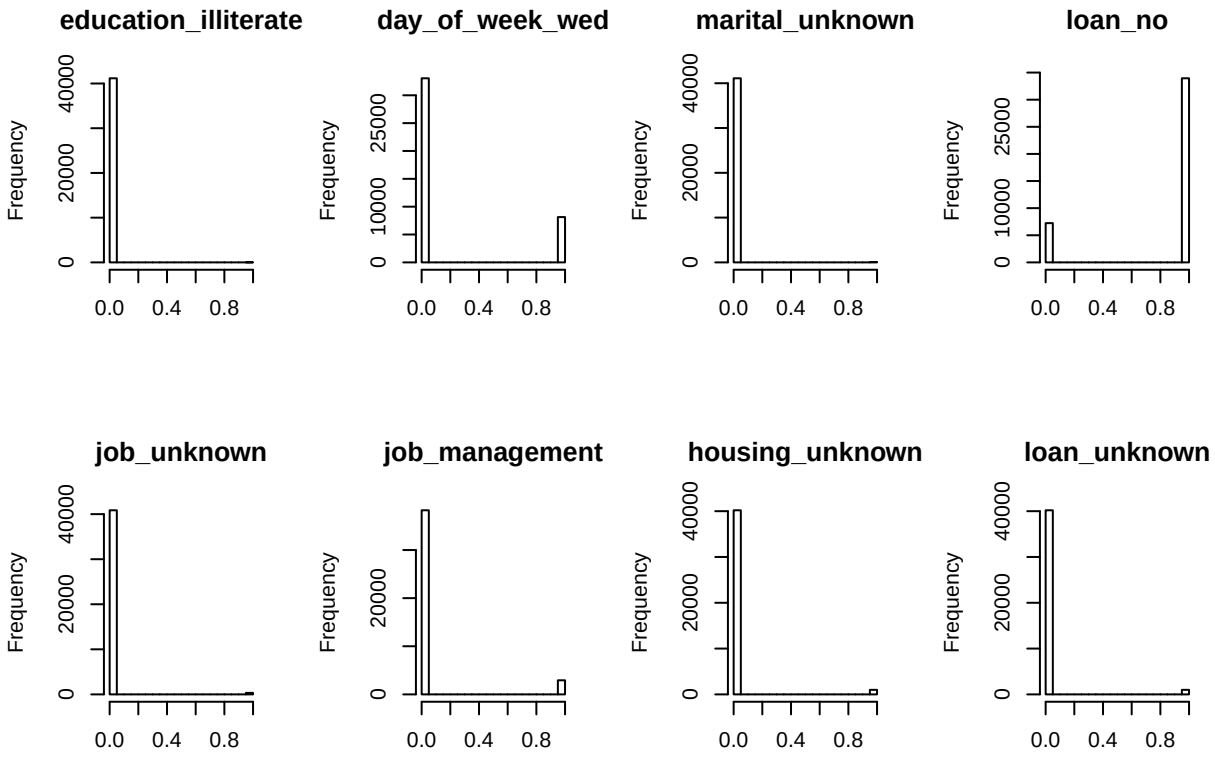
job_technician	-0.0061486
job_housemaid	-0.0065049
day_of_week_fri	-0.0069963
month_aug	-0.0088126
month_jun	-0.0091818
marital_divorced	-0.0106080
housing_no	-0.0110852
month_nov	-0.0117959
job_entrepreneur	-0.0166439
day_of_week_mon	-0.0212649
education_primary	-0.0237753
month_jul	-0.0322301
job_services	-0.0323009
education_secondary	-0.0394222
marital_married	-0.0433978
campaign	-0.0663574
job_blue-collar	-0.0744233
default_unknown	-0.0992934
month_may	-0.1082712
cons.price.idx	-0.1362112
contact_telephone	-0.1447731
poutcome_nonexistent	-0.1935068
emp.var.rate	-0.2983344
euribor3m	-0.3077714
pdays	-0.3249145
nr.employed	-0.3546783

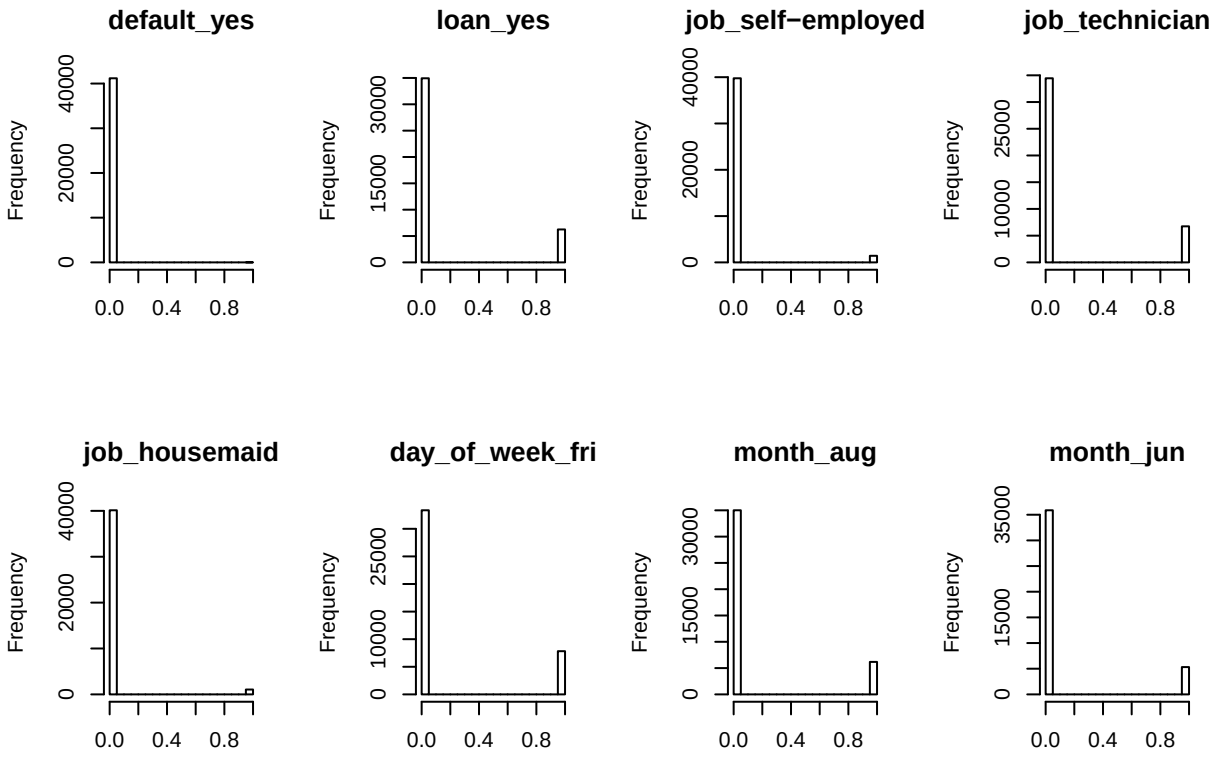
6.1.5 Outliers Analysis

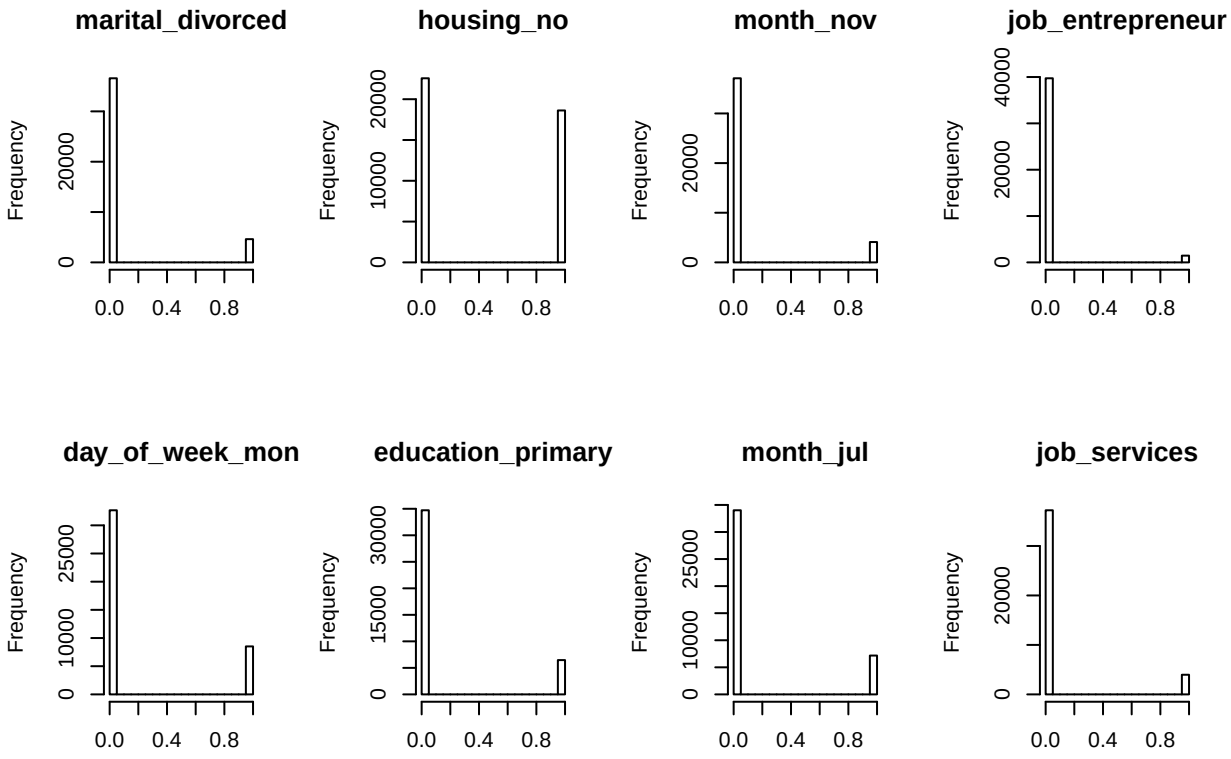


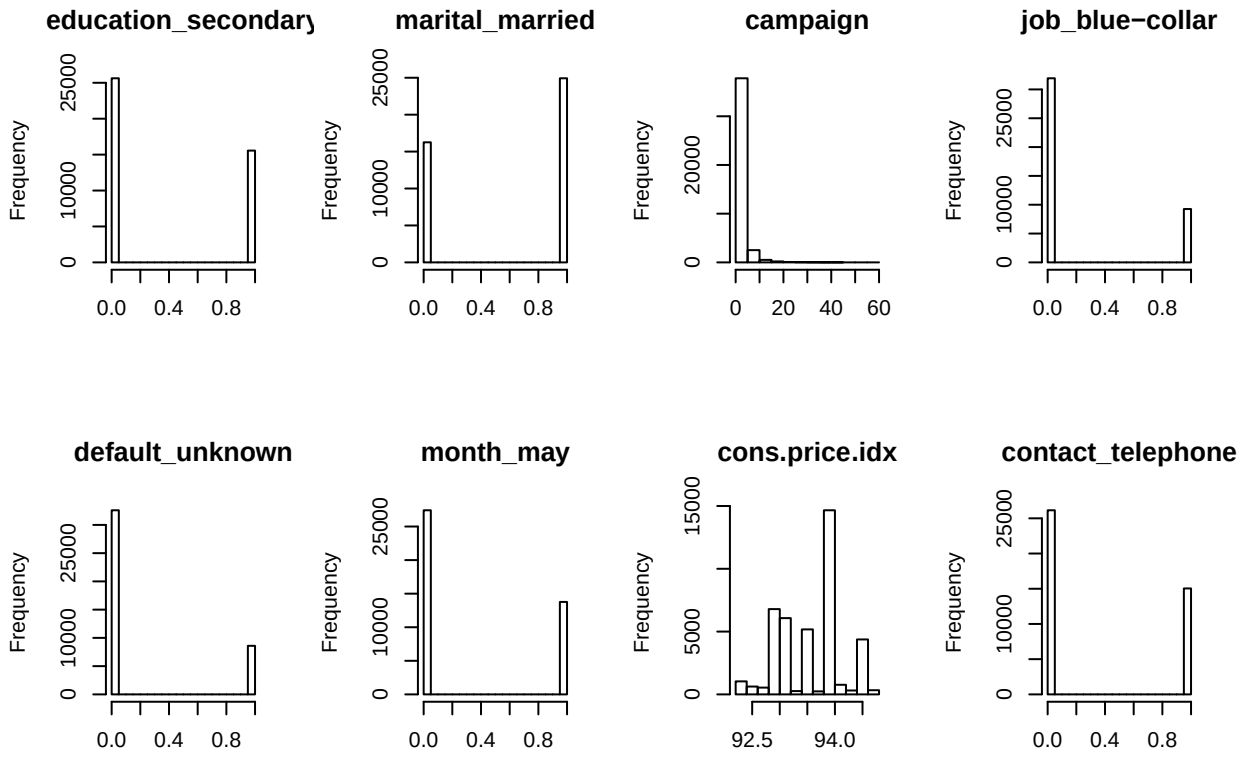

duration
previous_contact
poutcome_success
previous
contact_cellular
month_mar
month_oct
month_sep
default_no
job_student
job_retired
month_dec
month_apr
cons.conf.idx
marital_single
education_tertiary
Frequency

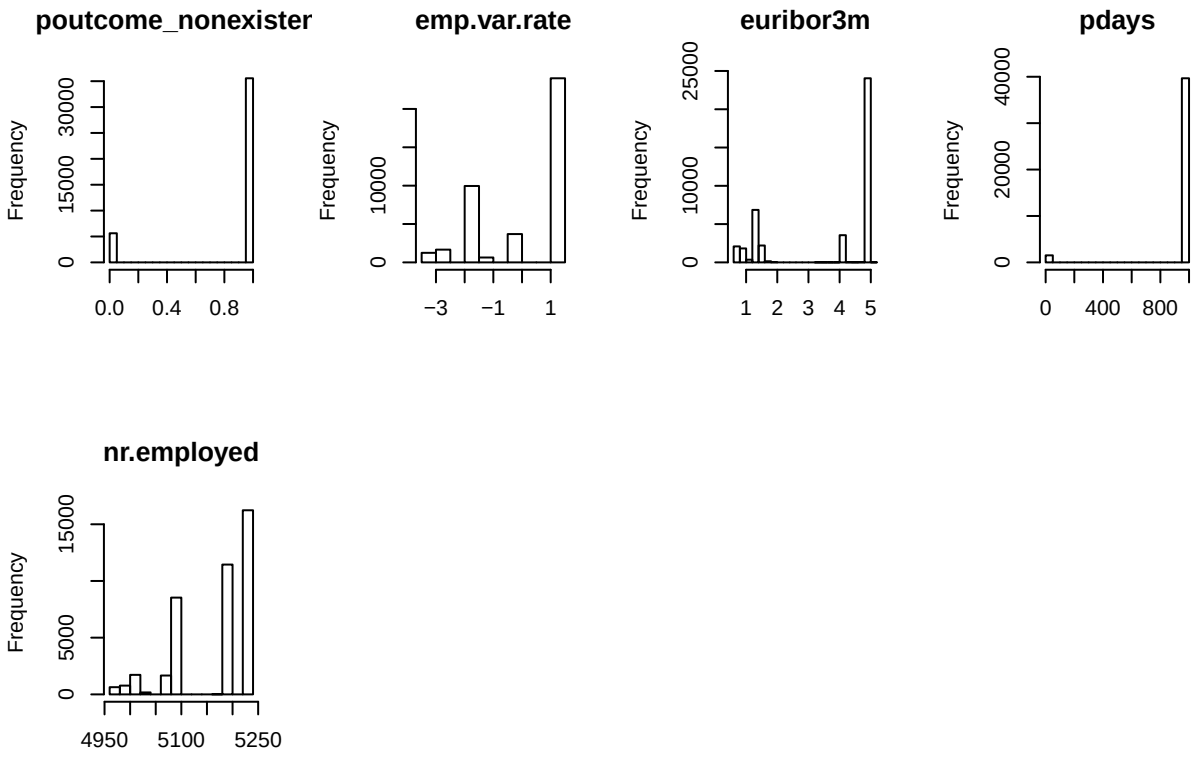

poutcome_failure
job_admin.
age
education_unknown
job_unemployed
day_of_week_thu
housing_yes
day_of_week_tue
Frequency
0
20000
40000
10000
25000
4000
8000
0.0
0.4
0.8
20
60
100


education_illiterate
day_of_week_wed
marital_unknown
loan_no
job_unknown
job_management
housing_unknown
loan_unknown
Frequency
0
20000
40000
10000
25000
0.0
0.4
0.8

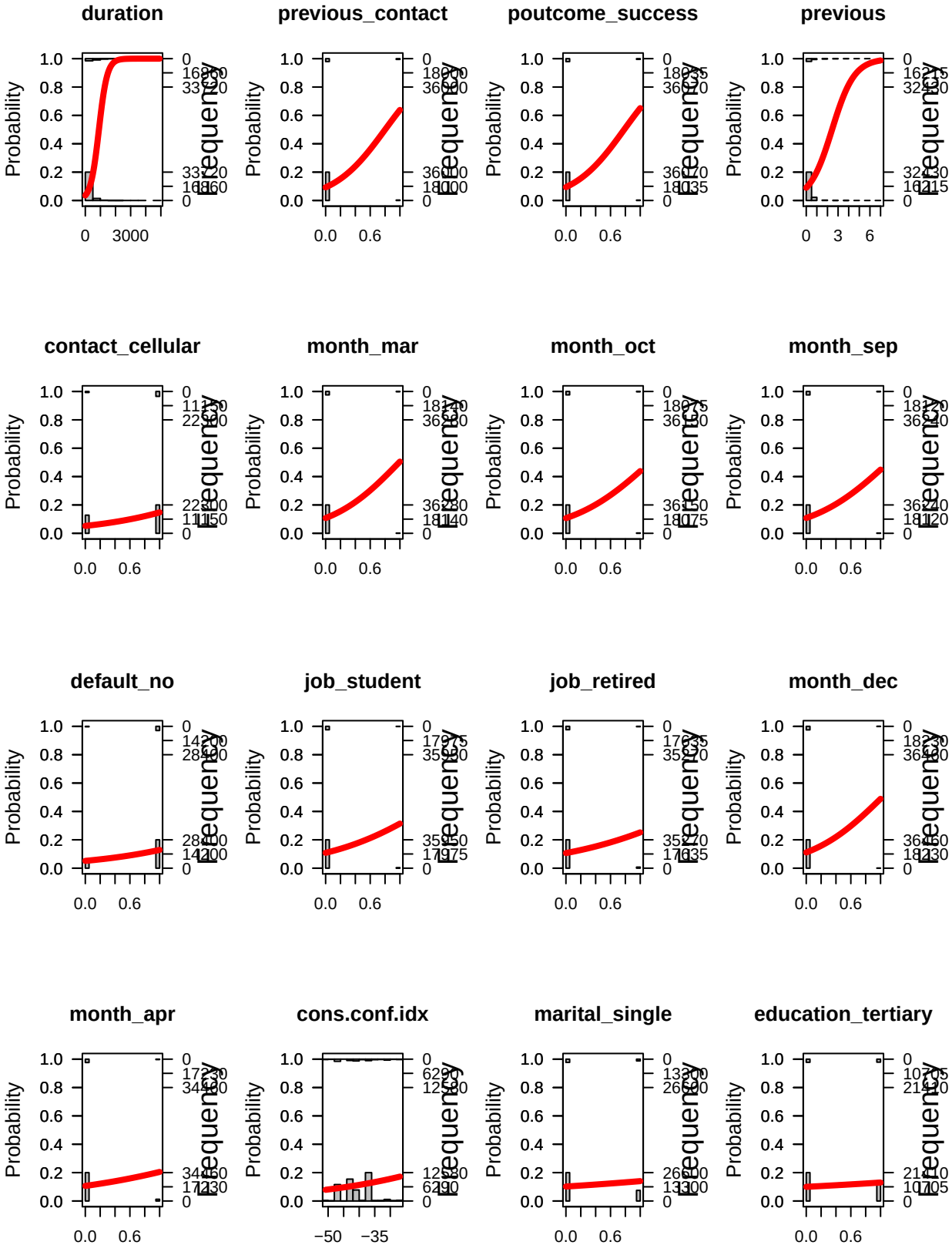

default_yes
loan_yes
job_self−employed
job_technician
job_housemaid
day_of_week_fri
month_aug
month_jun
Frequency
0.0
0.4
0.8

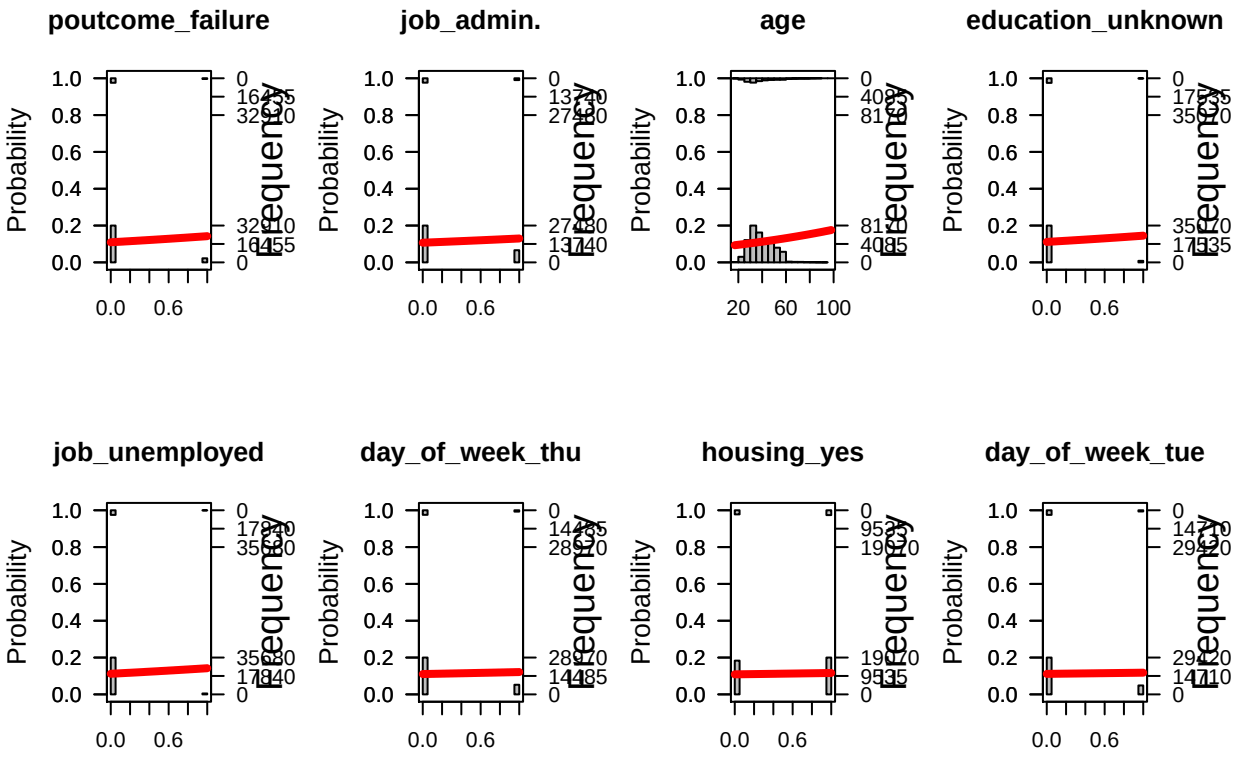

marital_divorced
housing_no
month_nov
job_entrepreneur
day_of_week_mon
education_primary
month_jul
job_services
Frequency
0.0
0.4
0.8

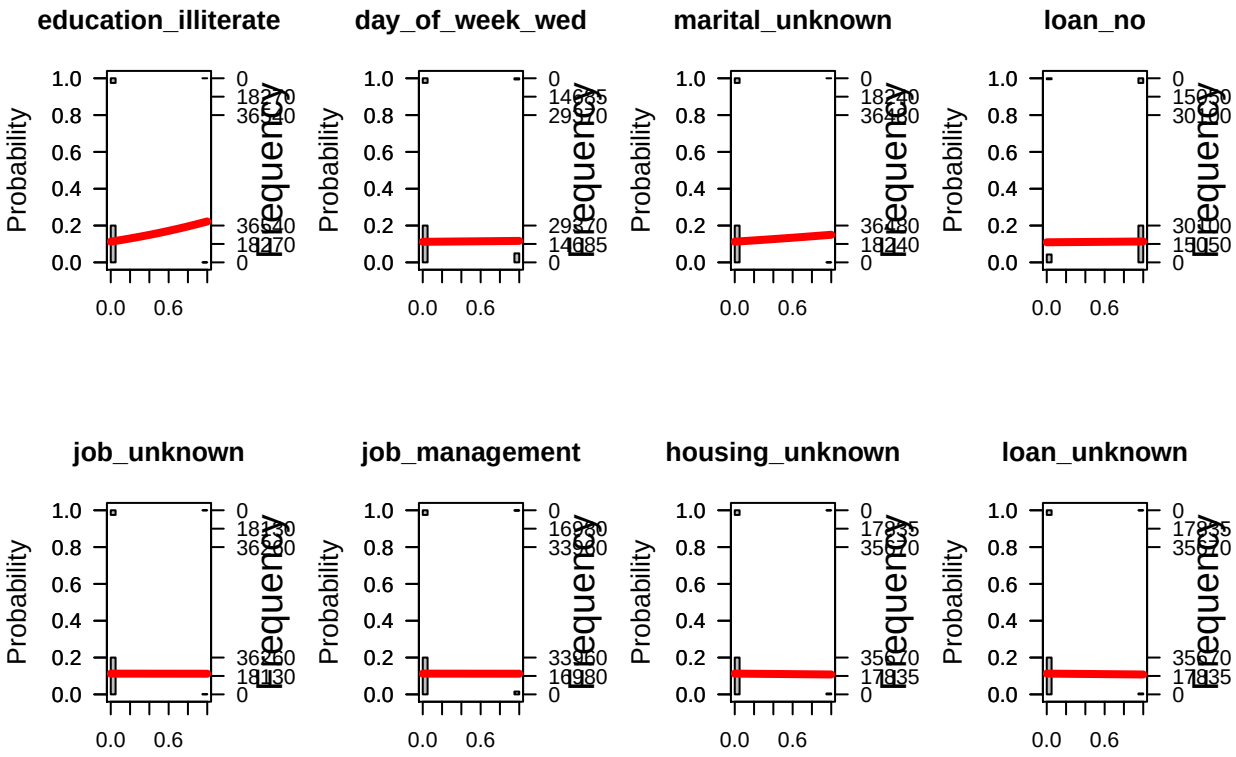

education_secondary
marital_married
campaign
job_blue−collar
default_unknown
month_may
cons.price.idx
contact_telephone
Frequency


poutcome_nonexister
Frequency
0
15000
30000
0.0
0.4
0.8
emp.var.rate
Frequency
0
10000
−3
−1
1
euribor3m
Frequency
0
10000
25000
1
2
3
4
5
pdays
Frequency
0
20000
40000
0
400
800
nr.employed
Frequency
0
5000
15000
4950
5100
5250

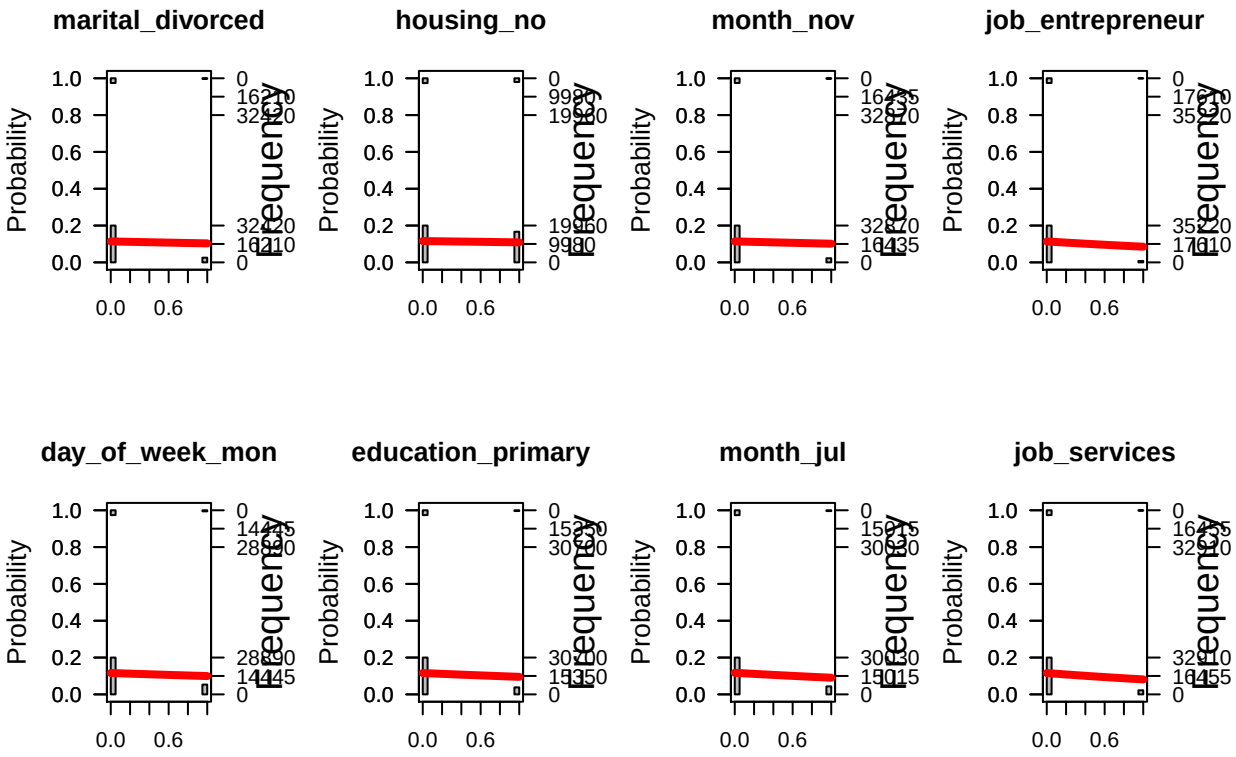
6.1.6 Analysis of link functions for given variables

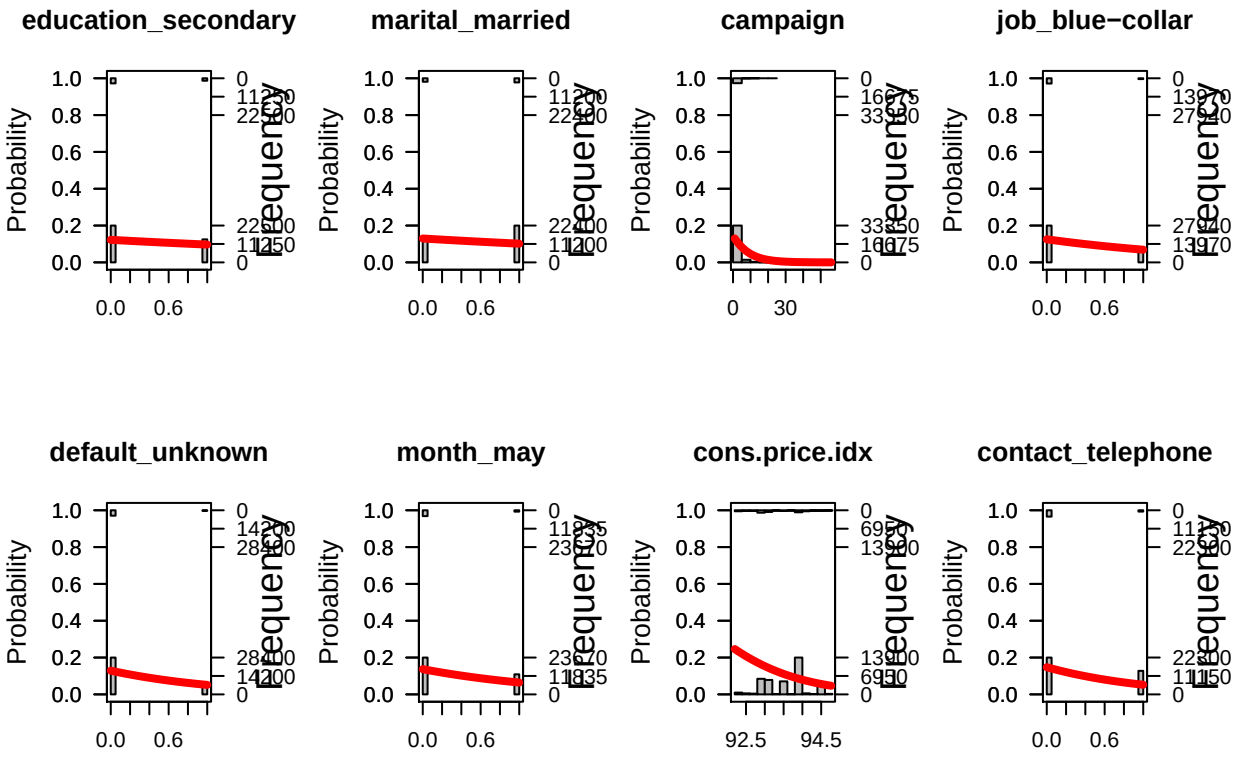


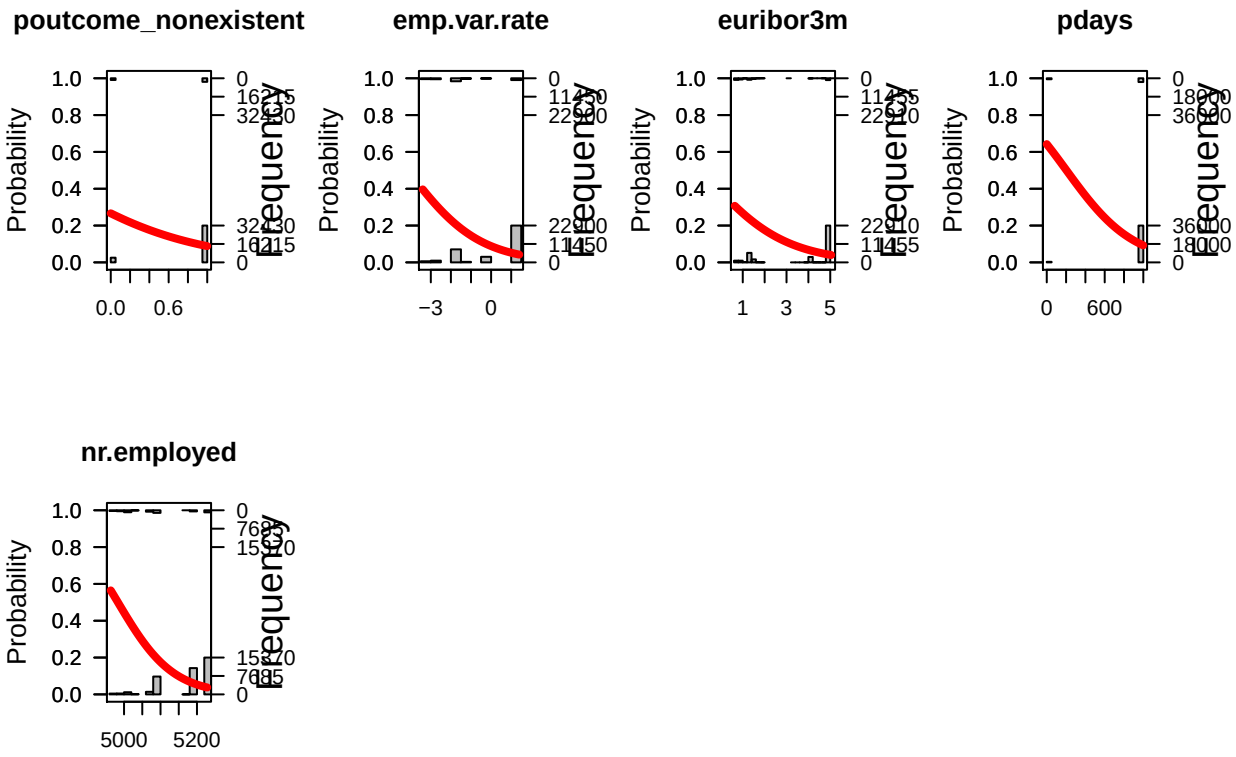

poutcome_failure
job_admin.
age
education_unknown
job_unemployed
day_of_week_thu
housing_yes
day_of_week_tue
Probability
Frequency


education_illiterate
day_of_week_wed
marital_unknown
loan_no
job_unknown
job_management
housing_unknown
loan_unknown
Probability
Frequency


default_yes
loan_yes
job_self−employed
job_technician
job_housemaid
day_of_week_fri
month_aug
month_jun
Probability
Frequency


marital_divorced
housing_no
month_nov
job_entrepreneur
day_of_week_mon
education_primary
month_jul
job_services
Probability
Frequency


education_secondary
marital_married
campaign
job_blue−collar
default_unknown
month_may
cons.price.idx
contact_telephone
Probability
Frequency


poutcome_nonexistent
emp.var.rate
euribor3m
pdays
nr.employed
Probability
Frequency