

# HW 9

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## 1 IST 387 HW 9

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```
[1]: # Enter your name here: Ezra Cohen
```

### 1.0.1 Attribution statement: (choose only one and delete the rest)

```
[2]: # 1. I did this homework by myself, with help from the book and the professor.
```

**Association mining** can be applied to many data problems beyond the well-known example of **finding relationships between different products in customer shopping data**. In this homework assignment, we will explore **real data** from the banking sector and look for **patterns associated with the likelihood of responding positively to a direct marketing campaign and signing up for a term deposit with the bank** (stored in the variable “y”). You can find out more about the variables in this dataset here: <https://archive.ics.uci.edu/ml/datasets/bank+marketing>

### 1.1 Part 1: Explore Data Set

- A. Copy the contents of the following URL to a dataframe called bank: <https://ist387.s3.us-east-2.amazonaws.com/data/bank-full.csv>

**Hint:** Even though this is a .csv file, chances are R won't be able to read it in correctly using the `read_csv()` function. If you take a closer look at the contents of the URL file, you may notice each field is separated by a **semicolon** (;) rather than a comma. In situations like this, consider using something like this:

```
[3]: url<-"https://ist387.s3.us-east-2.amazonaws.com/data/bank-full.csv"
bank <- read.table(url, sep=";", header = TRUE)
dim(bank)
bank
```

1. 41188 2. 21

	age <int>	job <chr>	marital <chr>	education <chr>	default <chr>	housing <chr>	loan <chr>
	56	housemaid	married	basic.4y	no	no	no
	57	services	married	high.school	unknown	no	no
	37	services	married	high.school	no	yes	no
	40	admin.	married	basic.6y	no	no	no
	56	services	married	high.school	no	no	yes
	45	services	married	basic.9y	unknown	no	no
	59	admin.	married	professional.course	no	no	no
	41	blue-collar	married	unknown	unknown	no	no
	24	technician	single	professional.course	no	yes	no
	25	services	single	high.school	no	yes	no
	41	blue-collar	married	unknown	unknown	no	no
	25	services	single	high.school	no	yes	no
	29	blue-collar	single	high.school	no	no	yes
	57	housemaid	divorced	basic.4y	no	yes	no
	35	blue-collar	married	basic.6y	no	yes	no
	54	retired	married	basic.9y	unknown	yes	yes
	35	blue-collar	married	basic.6y	no	yes	no
	46	blue-collar	married	basic.6y	unknown	yes	yes
	50	blue-collar	married	basic.9y	no	yes	yes
	39	management	single	basic.9y	unknown	no	no
	30	unemployed	married	high.school	no	no	no
	55	blue-collar	married	basic.4y	unknown	yes	no
	55	retired	single	high.school	no	yes	no
	41	technician	single	high.school	no	yes	no
	37	admin.	married	high.school	no	yes	no
	35	technician	married	university.degree	no	no	yes
	59	technician	married	unknown	no	yes	no
	39	self-employed	married	basic.9y	unknown	no	no
	54	technician	single	university.degree	unknown	no	no
A data.frame: 41188 × 21	55	unknown	married	university.degree	unknown	unknown	unknown
	35	technician	divorced	basic.4y	no	no	no
	35	technician	divorced	basic.4y	no	yes	no
	33	admin.	married	university.degree	no	no	no
	33	admin.	married	university.degree	no	yes	no
	60	blue-collar	married	basic.4y	no	yes	no
	35	technician	divorced	basic.4y	no	yes	no
	54	admin.	married	professional.course	no	no	no
	38	housemaid	divorced	university.degree	no	no	no
	32	admin.	married	university.degree	no	no	no
	32	admin.	married	university.degree	no	yes	no
	38	entrepreneur	married	university.degree	no	no	no
	62	services	married	high.school	no	yes	no
	40	management	divorced	university.degree	no	yes	no
	33	student	married	professional.course	no	yes	no
	31	admin.	single	university.degree	no	yes	no
	62	retired	married	university.degree	no	yes	no
	62	retired	married	university.degree	no	yes	no
	34	student	single	unknown	no	yes	no
	38	housemaid	divorced	high.school	no	yes	yes
	57	retired	married	professional.course	no	yes	no

Make sure there are **41,188** rows and **21** columns in your **bank** df.

- B. Next, we will focus on some key factor variables from the dataset, and convert a few numeric ones to factor variables. Execute the following commands and write a comment describing how the conversion for each numeric variable works and what the variables in the resulting dataframe are.

```
[4]: bank_new <- data.frame(job=bank$job,
                           marital=bank$marital,
                           housing_loan=bank$housing,
                           young=as.factor((bank$age<median(bank$age))),
                           #Makes it into a factor based on if the person is older or younger than the
                           ↳median of bank$age, if they are younger it is true if they are older it is
                           ↳false
                           contacted_more_than_once=as.factor((bank$campaign>1)),
                           #Makes it into a factor based on if they were contacted more than one times if
                           ↳they were contacted 1 or last times then it would be false and if they were
                           ↳contacted more than once it would be true
                           contacted_before_this_campaign=as.
                           ↳factor((bank$previous<0)),
                           #Makes it into a factor based on if they had less than zero Banks prior to
                           ↳this, and I don't understand the point of this because that doesn't seem
                           ↳possible and the entire column is just false
                           success=(bank$y))
bank_new
#Job is what job they do, marital is if they are married or not, housing loan
↳is whether they have a loan on their house, young is if they are young or
↳not, contacted more than once is if the bank contacted them more than once,
↳Contacted before this campaign is if they had less than zero banks prior to
↳this, and success is number of successful term deposit sign-up
```

	job <chr>	marital <chr>	housing_loan <chr>	young <fct>	contacted_more_than_once <fct>	com <fct>
	housemaid	married	no	FALSE	FALSE	FALSE
	services	married	no	FALSE	FALSE	FALSE
	services	married	yes	TRUE	FALSE	FALSE
	admin.	married	no	FALSE	FALSE	FALSE
	services	married	no	FALSE	FALSE	FALSE
	services	married	no	FALSE	FALSE	FALSE
	admin.	married	no	FALSE	FALSE	FALSE
	blue-collar	married	no	FALSE	FALSE	FALSE
	technician	single	yes	TRUE	FALSE	FALSE
	services	single	yes	TRUE	FALSE	FALSE
	blue-collar	married	no	FALSE	FALSE	FALSE
	services	single	yes	TRUE	FALSE	FALSE
	blue-collar	single	no	TRUE	FALSE	FALSE
	housemaid	divorced	yes	FALSE	FALSE	FALSE
	blue-collar	married	yes	TRUE	FALSE	FALSE
	retired	married	yes	FALSE	FALSE	FALSE
	blue-collar	married	yes	TRUE	FALSE	FALSE
	blue-collar	married	yes	FALSE	FALSE	FALSE
	blue-collar	married	yes	FALSE	FALSE	FALSE
	management	single	no	FALSE	FALSE	FALSE
	unemployed	married	no	TRUE	FALSE	FALSE
	blue-collar	married	yes	FALSE	FALSE	FALSE
	retired	single	yes	FALSE	FALSE	FALSE
	technician	single	yes	FALSE	FALSE	FALSE
	admin.	married	yes	TRUE	FALSE	FALSE
	technician	married	no	TRUE	FALSE	FALSE
	technician	married	yes	FALSE	FALSE	FALSE
	self-employed	married	no	FALSE	FALSE	FALSE
	technician	single	no	FALSE	TRUE	FALSE
A data.frame: 41188 × 7	unknown	married	unknown	FALSE	FALSE	FALSE
	technician	divorced	no	TRUE	FALSE	FALSE
	technician	divorced	yes	TRUE	FALSE	FALSE
	admin.	married	no	TRUE	FALSE	FALSE
	admin.	married	yes	TRUE	FALSE	FALSE
	blue-collar	married	yes	FALSE	TRUE	FALSE
	technician	divorced	yes	TRUE	TRUE	FALSE
	admin.	married	no	FALSE	TRUE	FALSE
	housemaid	divorced	no	FALSE	TRUE	FALSE
	admin.	married	no	TRUE	FALSE	FALSE
	admin.	married	yes	TRUE	TRUE	FALSE
	entrepreneur	married	no	FALSE	TRUE	FALSE
	services	married	yes	FALSE	TRUE	FALSE
	management	divorced	yes	FALSE	TRUE	FALSE
	student	married	yes	TRUE	FALSE	FALSE
	admin.	single	yes	TRUE	FALSE	FALSE
	retired	married	yes	FALSE	FALSE	FALSE
	retired	married	yes	FALSE	FALSE	FALSE
	student	single	yes	TRUE	FALSE	FALSE
	housemaid	divorced	yes	FALSE	FALSE	FALSE
	retired	married	yes	FALSE	TRUE	FALSE

C. Count the number of successful term deposit sign-ups, using the `table( )` command on the **success** variable.

```
[5]: table(bank_new$success)
```

```
      no    yes  
36548  4640
```

D. Express the results of problem C as percentages by sending the results of the `table( )` command into the `prop.table( )` command.

```
[6]: prop.table(table(bank_new$success))
```

```
      no        yes  
0.8873458 0.1126542
```

E. Using the same techniques, show the percentages for the **marital** and **housing\_loan** variables as well.

```
[7]: prop.table(table(bank_new$marital))  
     prop.table(table(bank_new$housing_loan))
```

```
      divorced      married      single      unknown  
0.111974361 0.605224823 0.280858502 0.001942313
```

```
      no      unknown      yes  
0.45212198 0.02403613 0.52384190
```

## 1.2 Part 2: Coerce the data frame into transactions

F. Install and library two packages: **arules** and **arulesViz**.

```
[21]: #install.packages("arules")  
      #install.packages("arulesViz")  
      library(arules)  
      library(arulesViz)
```

G. Coerce the **bank\_new** dataframe into a **sparse transactions matrix** called **bankX**.

```
[9]: bankx<-as(bank_new, "transactions")
```

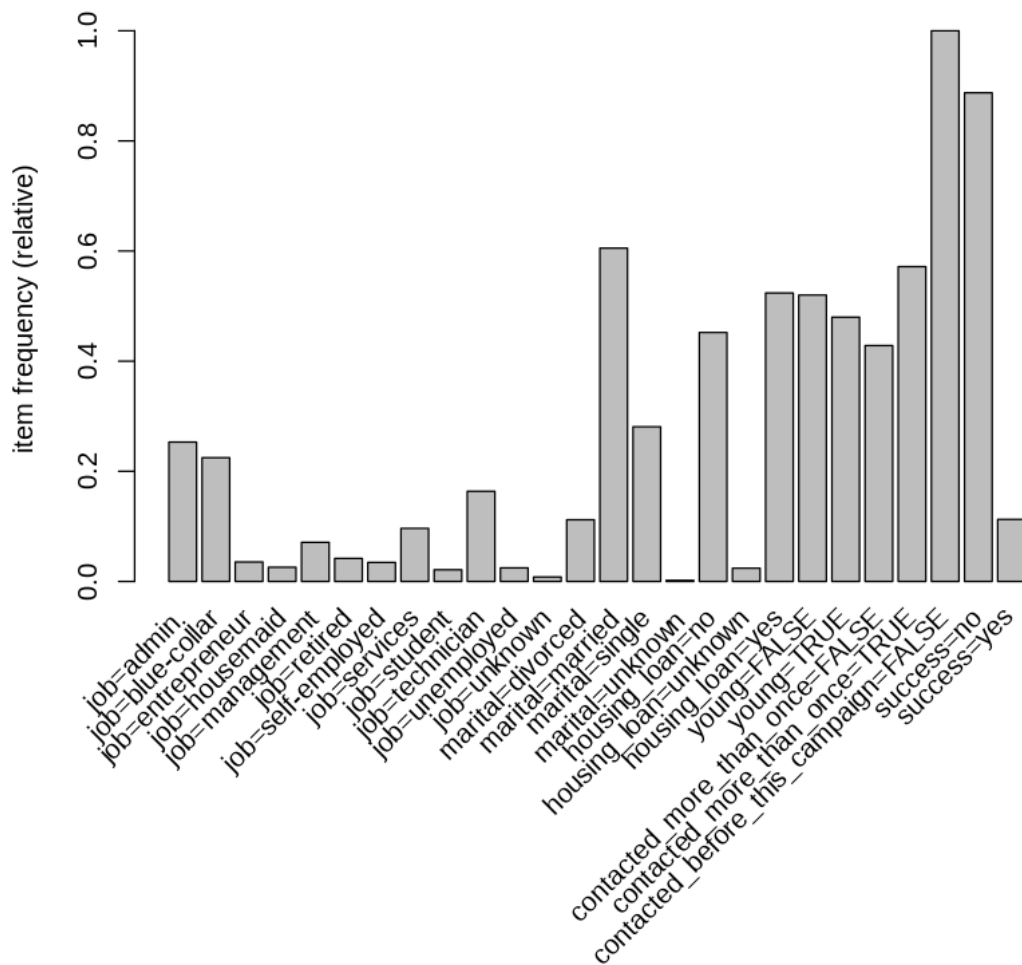
Warning message:

```
"Column(s) 1, 2, 3, 7 not logical or factor. Applying default discretization  
(see '? discretizeDF')."
```

H. Use the `itemFrequency( )` and `itemFrequencyPlot( )` commands to explore the contents of **bankX**. What do you see?

```
[10]: itemFrequency(bankx)
      itemFrequencyPlot(bankx)
#From this we can see what occurred in what percent of the cases and we can get
↪ information like a majority of the people have a job as admin, most of them
↪ have a marital status of married, and and way more people have success as a
↪ no then as a yes
```

```
job=admin.    0.253034864523648 job=blue-collar    0.224677090414684 job=entrepreneur
0.035350101971448 job=housemaid                    0.0257356511605322 job=management
0.0709915509371662 job=retired 0.0417597358453919 job=self-employed 0.0345003399048266
job=services    0.0963630183548606 job=student    0.0212440516655336 job=technician
0.16371273186365 job=unemployed 0.0246188210158299 job=unknown 0.00801204234242983
marital=divorced 0.111974361464504 marital=married 0.605224822763912 marital=single
0.280858502476449 marital=unknown                    0.00194231329513451 housing\__loan=no
0.452121977274934 housing\__loan=unknown            0.0240361270272895 housing\__loan=yes
0.523841895697776 young=FALSE 0.520054384772264 young=TRUE 0.479945615227736
contacted\__more\__than\__once=FALSE                0.428328639409537
contacted\__more\__than\__once=TRUE                  0.571671360590463
contacted\__before\__this\__campaign=FALSE          1 success=no 0.887345828882199
success=yes                                          0.112654171117801
```



I. This is a fairly large dataset, so we will explore only the first 10 observations in the **bankX** transaction matrix:

```
[11]: inspect(bankx[1:10])
```

	items	transactionID
[1]	{job=housemaid, marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	1
[2]	{job=services,	

	marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	2
[3]	{job=services, marital=married, housing_loan=yes, young=TRUE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	3
[4]	{job=admin., marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	4
[5]	{job=services, marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	5
[6]	{job=services, marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	6
[7]	{job=admin., marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	7
[8]	{job=blue-collar, marital=married, housing_loan=no, young=FALSE, contacted_more_than_once=FALSE, contacted_before_this_campaign=FALSE, success=no}	8



```
[9] {job=technician,
    marital=single,
    housing_loan=yes,
    young=TRUE,
    contacted_more_than_once=FALSE,
    contacted_before_this_campaign=FALSE,
    success=no} 9
```

```
[10] {job=services,
    marital=single,
    housing_loan=yes,
    young=TRUE,
    contacted_more_than_once=FALSE,
    contacted_before_this_campaign=FALSE,
    success=no} 10
```

Explain the difference between **bank\_new** and **bankX** in a block comment:

Bank\_new is a data set and Bankx is a sparse transactions Matrix

### 1.3 Part 3: Use arules to discover patterns

**Support** is the proportion of times that a particular set of items occurs relative to the whole dataset. **Confidence** is proportion of times that the consequent occurs when the antecedent is present.

- J. Use **apriori** to generate a set of rules with support over 0.005 and confidence over 0.3, and trying to predict who successfully signed up for a term deposit. **Hint:** You need to define the **right-hand side rule (rhs)**.

```
[50]: ruleset<-apriori(bankx,
                      parameter=list(supp=0.006, conf=0.32),
                      control=list(verbose=F),
                      appearance=list(default="lhs",rhs=("success=yes")))
```

- K. Use `inspect()` to review of the **ruleset**.

```
[51]: inspect(ruleset)
```

lhs	confidence	coverage	lift	count	rhs	support
[1] {job=student, marital=single}	0.3203883	0.02000583	2.843999	264	=> {success=yes}	0.006409634
[2] {job=student, marital=single, young=TRUE}	0.3233831	0.01952025	2.870582	260	=> {success=yes}	0.006312518
[3] {job=student, marital=single, contacted_before_this_campaign=FALSE}					=> {success=yes}	0.006409634

```

0.3203883 0.02000583 2.843999    264
[4] {job=student,
     marital=single,
     young=TRUE,
     contacted_before_this_campaign=FALSE} => {success=yes} 0.006312518
0.3233831 0.01952025 2.870582    260

```

L. Use the output of `inspect( )` or `inspectDT( )` and describe **any 2 rules** the algorithm found.

All of these rules are very similar so it would be difficult to discuss two separate rules so I will just discuss the last rule which includes everything from all the prior rules, this rule includes the job is student, the marital status is single, young is true, and contacted prior to Campaign is false, all of these things make sense together, someone who is a student is likely to be young and single and everyone was not contacted prior to the campaign so it would be false for everyone, and what all of this is implying is that younger less experienced people are more likely to sign up for it