

AED

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```
load("C:/Users/34688/OneDrive - Universitat de Barcelona/Escritorio/Mineria/DATA/data.RData")
library(ggplot2)
library(psych)
```

Anàlisis univariante

Univariante Numèrica

Univariante Categòrica

Anàlisis bivariante

Es realitzarà un estudi a dos dimensions per trobar possibles relacions interessants.

Numèrica i numèrica

Estudiarem la correlació entre les varibales numèriques.

```
cor(data[, varNum], use = "pairwise.complete.obs")
```

##		Age	CreditScore	Tenure	EstimatedSalary
## Age	1.0000000000	-1.288793e-02	-0.011927920	0.0043640775	
## CreditScore	-0.0128879311	1.000000e+00	0.012452797	-0.0004280996	
## Tenure	-0.0119279205	1.245280e-02	1.0000000000	0.0123469012	
## EstimatedSalary	0.0043640775	-4.280996e-04	0.012346901	1.0000000000	
## Balance	0.0370722102	3.365710e-03	-0.007427842	0.0233364866	
## NumOfProducts	-0.0236431172	2.147604e-02	0.017258959	0.0185216576	
## TransactionFrequency	-0.0015204986	7.914231e-03	0.018024611	0.0086363209	
## AvgTransactionAmount	-0.0011060698	3.931344e-02	-0.006490741	-0.0002324889	
## DigitalEngagementScore	-0.0208434404	9.183578e-05	0.008434622	-0.0085572580	
## ComplaintsCount	-0.0150222405	3.475790e-04	0.002818873	0.0007486169	
## NetPromoterScore	0.0009555647	-1.192457e-02	-0.006851175	-0.0099860853	
##		Balance	NumOfProducts	TransactionFrequency	
## Age	0.037072210	-0.023643117	-0.001520499		
## CreditScore	0.003365710	0.021476040	0.007914231		
## Tenure	-0.007427842	0.017258959	0.018024611		
## EstimatedSalary	0.023336487	0.018521658	0.008636321		
## Balance	1.000000000	-0.314486243	-0.003322540		
## NumOfProducts	-0.314486243	1.000000000	-0.002818329		
## TransactionFrequency	-0.003322540	-0.002818329	1.000000000		
## AvgTransactionAmount	0.005062801	-0.025388200	0.006821174		
## DigitalEngagementScore	-0.019772640	-0.015163911	0.020503983		
## ComplaintsCount	0.021986472	-0.018400137	0.016389856		

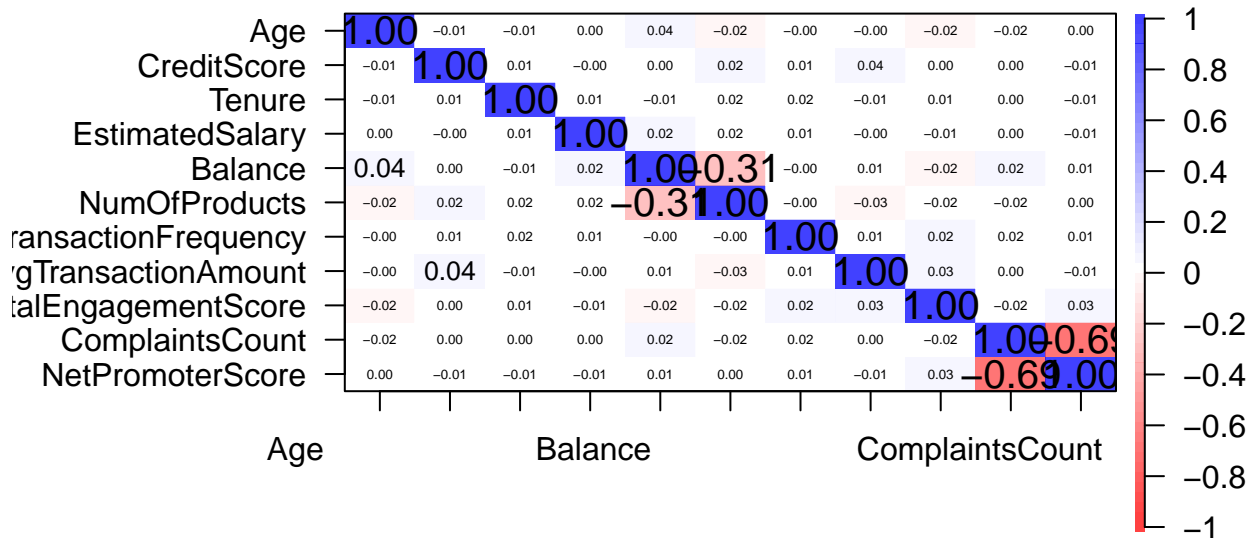
```

## NetPromoterScore      0.012125535    0.002440939      0.007265435
##                      AvgTransactionAmount DigitalEngagementScore
## Age                  -0.0011060698      -2.084344e-02
## CreditScore          0.0393134350       9.183578e-05
## Tenure               -0.0064907411       8.434622e-03
## EstimatedSalary      -0.0002324889      -8.557258e-03
## Balance              0.0050628014      -1.977264e-02
## NumOfProducts        -0.0253881998      -1.516391e-02
## TransactionFrequency  0.0068211743       2.050398e-02
## AvgTransactionAmount  1.0000000000       2.727683e-02
## DigitalEngagementScore 0.0272768254       1.000000e+00
## ComplaintsCount       0.0024675876      -1.649286e-02
## NetPromoterScore     -0.0125723111       2.514659e-02
##                      ComplaintsCount NetPromoterScore
## Age                  -0.0150222405      0.0009555647
## CreditScore          0.0003475790      -0.0119245738
## Tenure               0.0028188733      -0.0068511752
## EstimatedSalary      0.0007486169      -0.0099860853
## Balance              0.0219864718      0.0121255346
## NumOfProducts        -0.0184001371      0.0024409386
## TransactionFrequency  0.0163898562      0.0072654348
## AvgTransactionAmount  0.0024675876      -0.0125723111
## DigitalEngagementScore -0.0164928593      0.0251465852
## ComplaintsCount       1.0000000000      -0.6914615774
## NetPromoterScore     -0.6914615774      1.0000000000

```

```
corPlot(data[, varNum])
```

Correlation plot from data



S'observa que majoritariamente les variables no estan correlacionades, totes amb valors propers a 0. Excepte dos casos, una correlació negativa entre ComplaintsCount i NetPromoterScore de -0.69 i Balance amb NumOfProducts de -0.31. Com s'ha comentat previament, la variable NumOfProducts i ComplaintsCount possiblement es transformarà com a variable categòrica, llavors, no es realitzà cap canvi aquí.

Categòrica i categòrica

S'ha estudiat la relació entre la variable resposta Exited i la resta de variables categòriques.

```
cat<-varCat[-10]
v<-"Exited"
par(mfrow = c(3, 3))
for (varc1 in cat) {
  if (varc1 != v) {
    prop_table <- prop.table(table(data[, v], data[, varc1]),margin = 2)
    print(prop_table)
    barplot(prop_table, beside = TRUE,main = paste0(v,"&",varc1))
  }
}
```

```
##
##      France  Germany  Spain
## 0 0.8331288 0.6858766 0.8233851
## 1 0.1668712 0.3141234 0.1766149
##
##      Female  Male
## 0 0.7326467 0.8293963
```

```

## 1 0.2673533 0.1706037
##
##      Divorced      Married      Single      Widowed
## 0 0.7932489 0.7966903 0.7925718 0.7633929
## 1 0.2067511 0.2033097 0.2074282 0.2366071
##
##      High School      Other Postgraduate University
## 0 0.7919180 0.7511521 0.7826087 0.7811271
## 1 0.2080820 0.2488479 0.2173913 0.2188729
##
##              0              1
## 0 0.7756498 0.7946481
## 1 0.2243502 0.2053519
##
##              0              1
## 0 0.7945455 0.7895385
## 1 0.2054545 0.2104615
##
##      Active loan Default risk      No loan
## 0 0.7923729 0.7947154 0.7984626
## 1 0.2076271 0.2052846 0.2015374
##
##      Affluent High Net Worth Mass Market
## 0 0.7908127 0.7778970 0.8014101
## 1 0.2091873 0.2221030 0.1985899
##
##              0              1
## 0 0.7297412 0.8537161
## 1 0.2702588 0.1462839

```



S'observa que la distribució de la variable resposta és molt similar dins de cada grup excepte alguns. A través del gràfic de barres es veu la variable Geography, IsActiveMember i Gender tenen una diferencia considerable i obtenim les conclusions següents.

- Els d'origen alemany tenen aproximadament 1/3 de probabilitat de marxar.
- Les dones marxen amb més probabilitat.
- Els membres no actius tenen una prob més elevada de marxar.

S'ha realitzat el test de chi-quadrat per tal de veure si la diferencia observada és significativa.

```
for (varc1 in cat) {
  if (varc1 != v) {
    tab <- table(data[[v]], data[[varc1]])
    test <- chisq.test(tab, correct = FALSE)

    cat("\nVariable:", varc1, "\n")
    cat("Chi-squared =", round(test$statistic, 3),
        "df =", test$parameter,
        "p-value =", signif(test$p.value, 5), "\n")

    if (test$p.value < 0.05) cat("-> Diferencias significativas entre columnas\n")
  }
}
```

```
##
## Variable: Geography
## Chi-squared = 117.259 df = 2 p-value = 3.4475e-26
## -> Diferencias significativas entre columnas
```

```
##
## Variable: Gender
## Chi-squared = 67.477 df = 1 p-value = 2.1316e-16
## -> Diferencias significativas entre columnas
##
## Variable: MaritalStatus
## Chi-squared = 1.404 df = 3 p-value = 0.70451
##
## Variable: EducationLevel
## Chi-squared = 2.111 df = 3 p-value = 0.54968
##
## Variable: HasCrCard
## Chi-squared = 2.224 df = 1 p-value = 0.1359
##
## Variable: SavingsAccountFlag
## Chi-squared = 0.166 df = 1 p-value = 0.68361
##
## Variable: LoanStatus
## Chi-squared = 0.229 df = 2 p-value = 0.89203
##
## Variable: CustomerSegment
## Chi-squared = 2.421 df = 2 p-value = 0.29805
##
## Variable: IsActiveMember
## Chi-squared = 114.979 df = 1 p-value = 7.9551e-27
## -> Diferencias significativas entre columnas
```

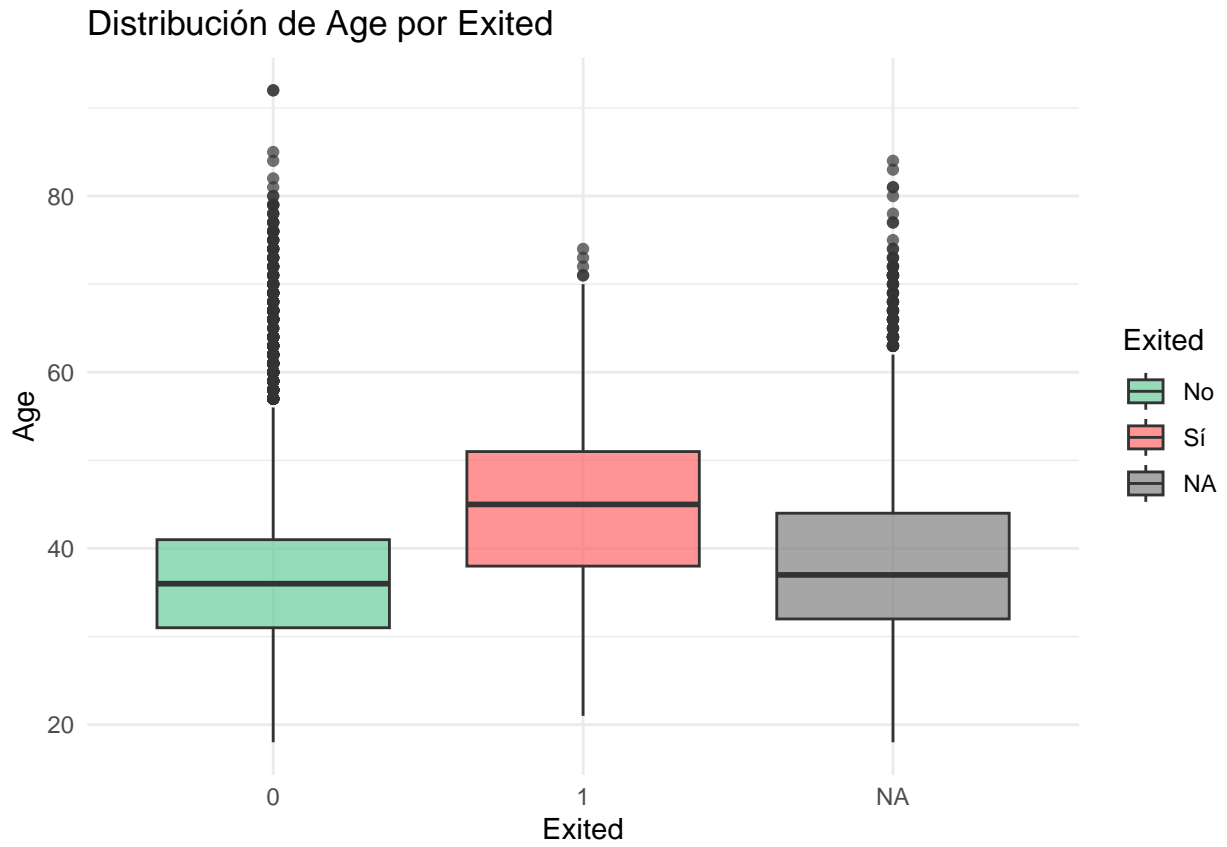
Un cop fet el test, s'afirma lo que s'ha concluint anteriorment.

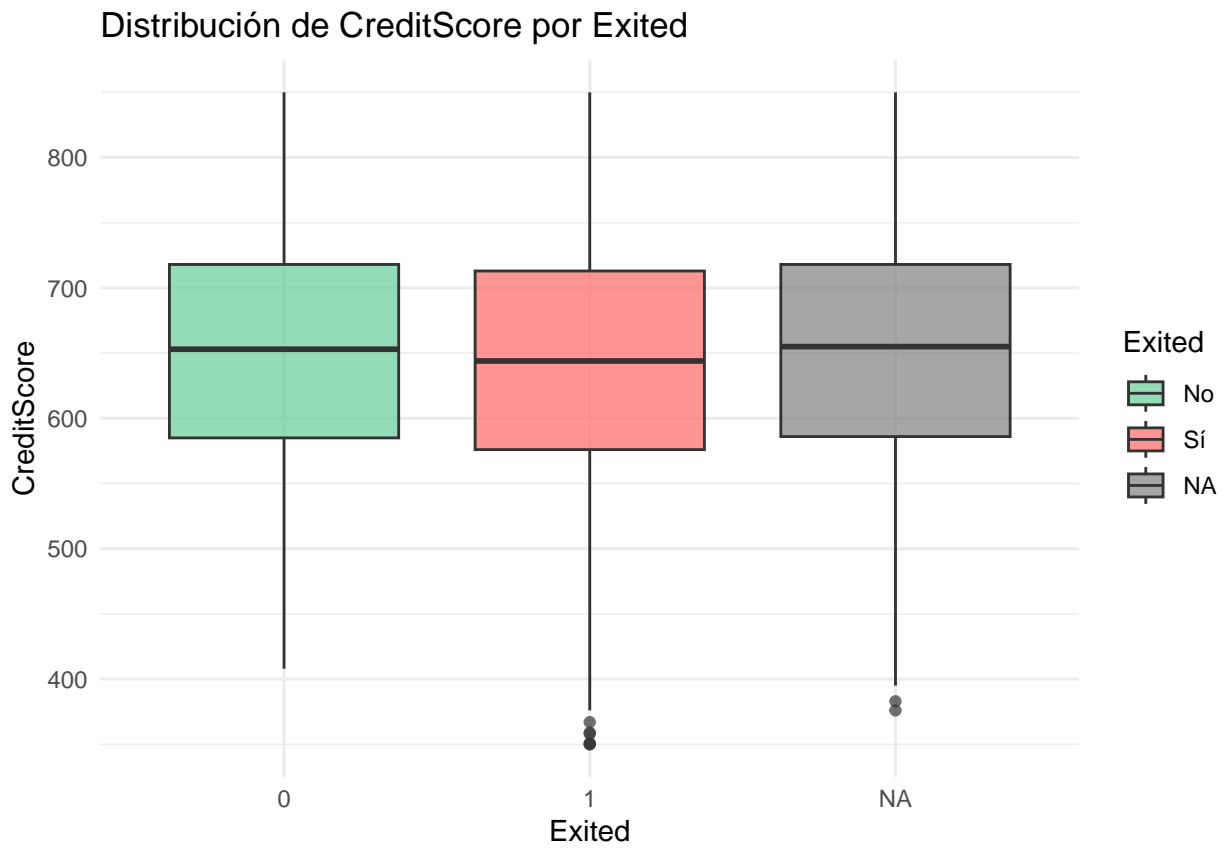
Numèrica i categòrica

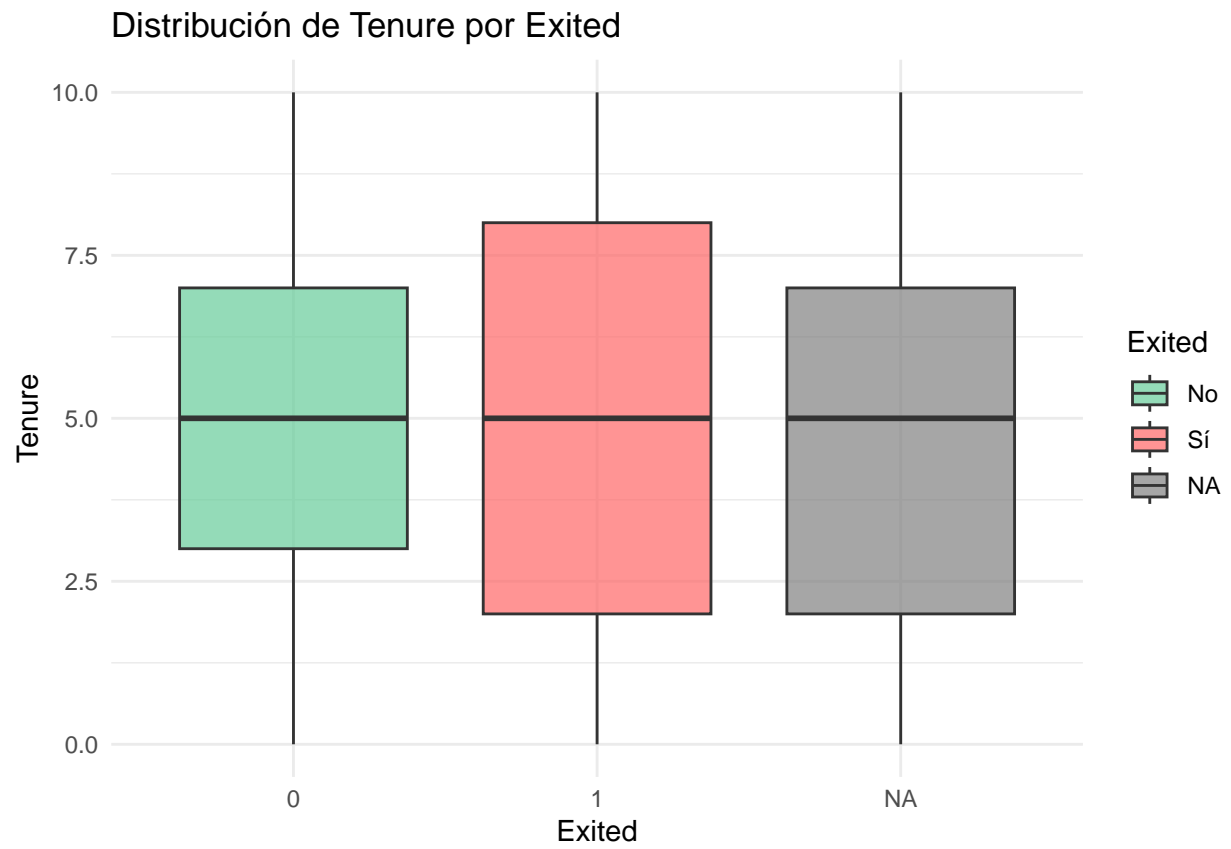
Estudiem la variable resposta amb la resta de variables numèriques.

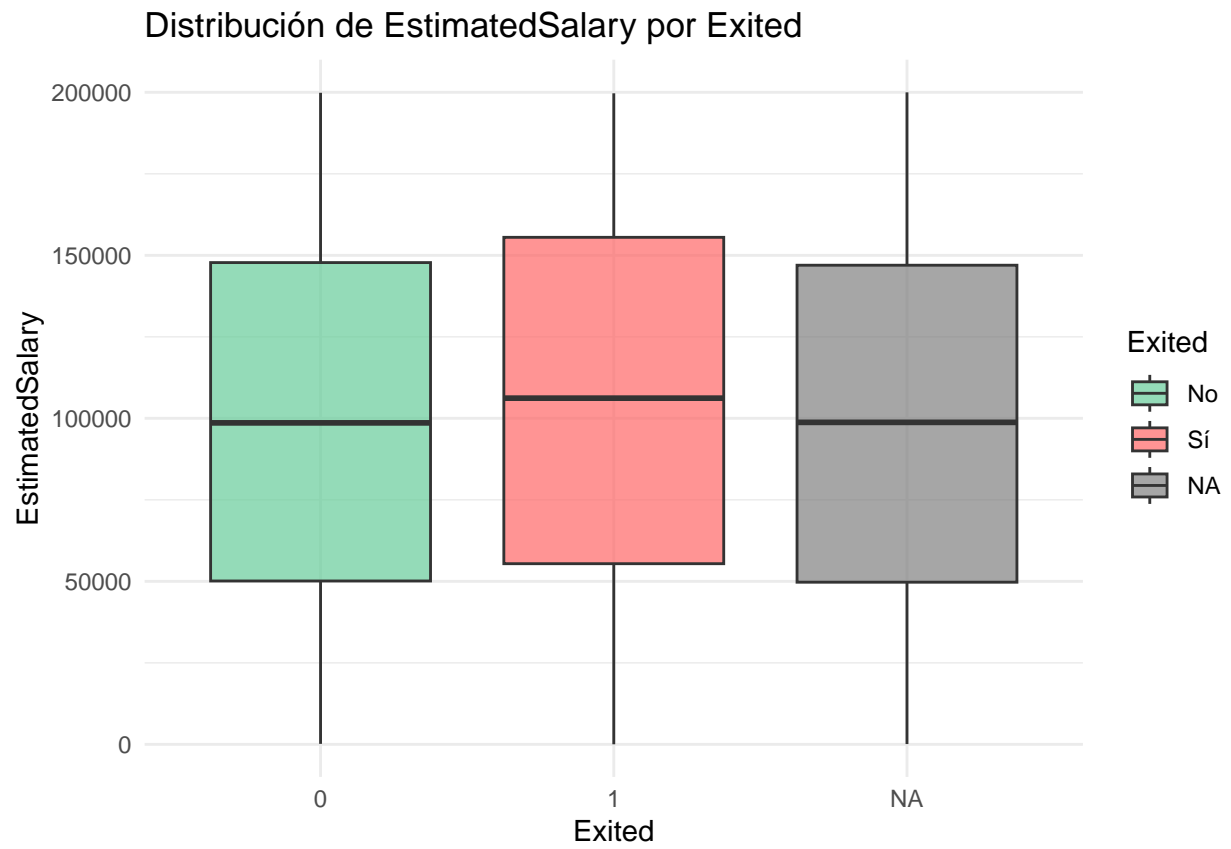
```
for (var in varNum) {
  p <- ggplot(data, aes(x = factor(Exited), y = .data[[var]], fill = factor(Exited))) +
    geom_boxplot(alpha = 0.7, na.rm = TRUE) +
    labs(x = "Exited",
         y = var,
         title = paste("Distribución de", var, "por Exited")) +
    scale_fill_manual(values = c("#66CC99", "#FF6666"),
                      name = "Exited",
                      labels = c("No", "Sí")) +
    theme_minimal()

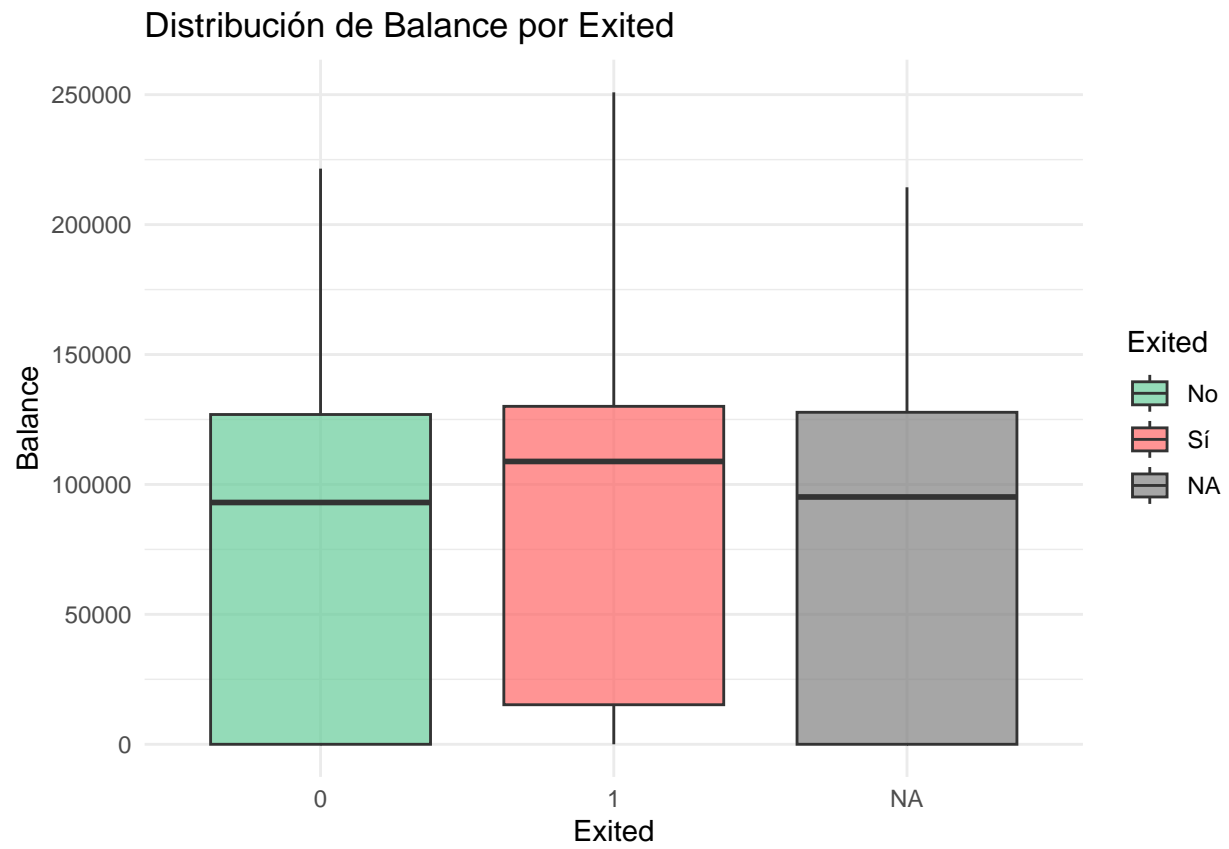
  print(p)
}
```

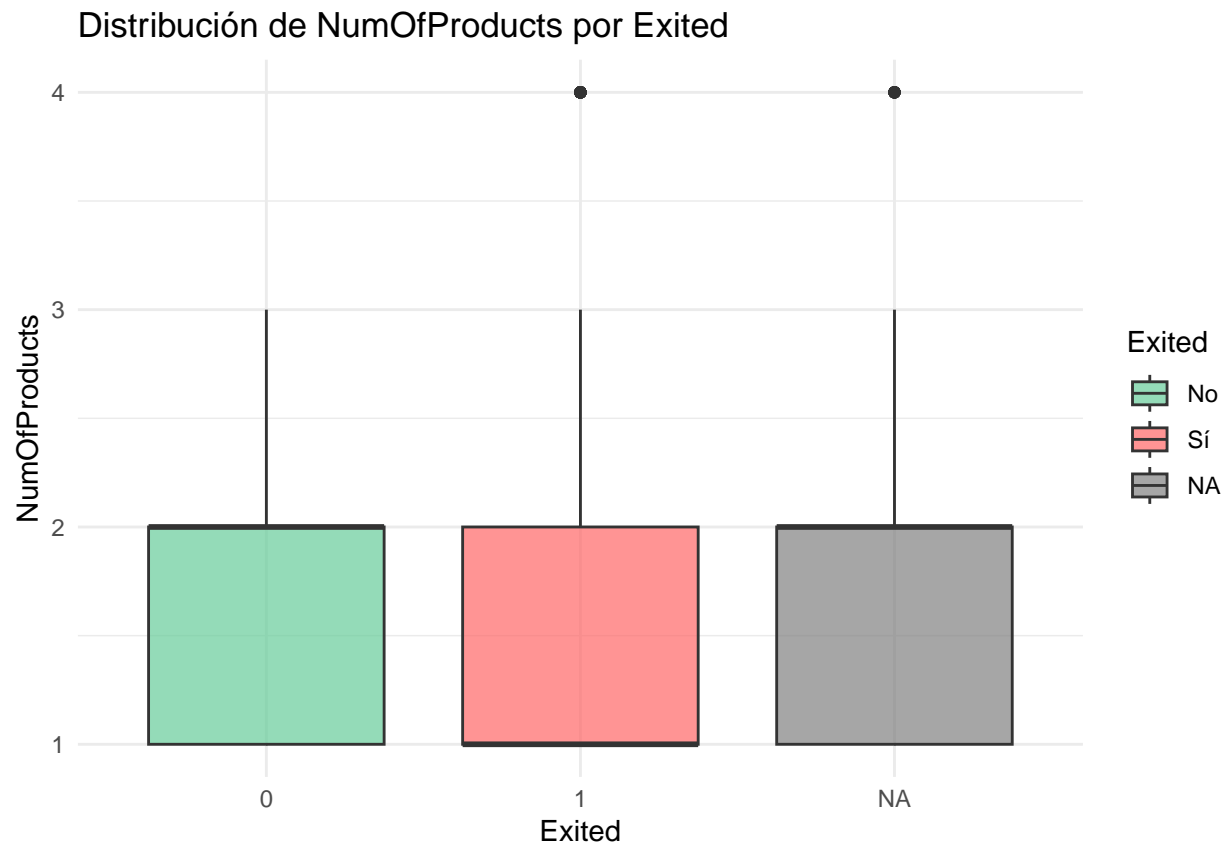


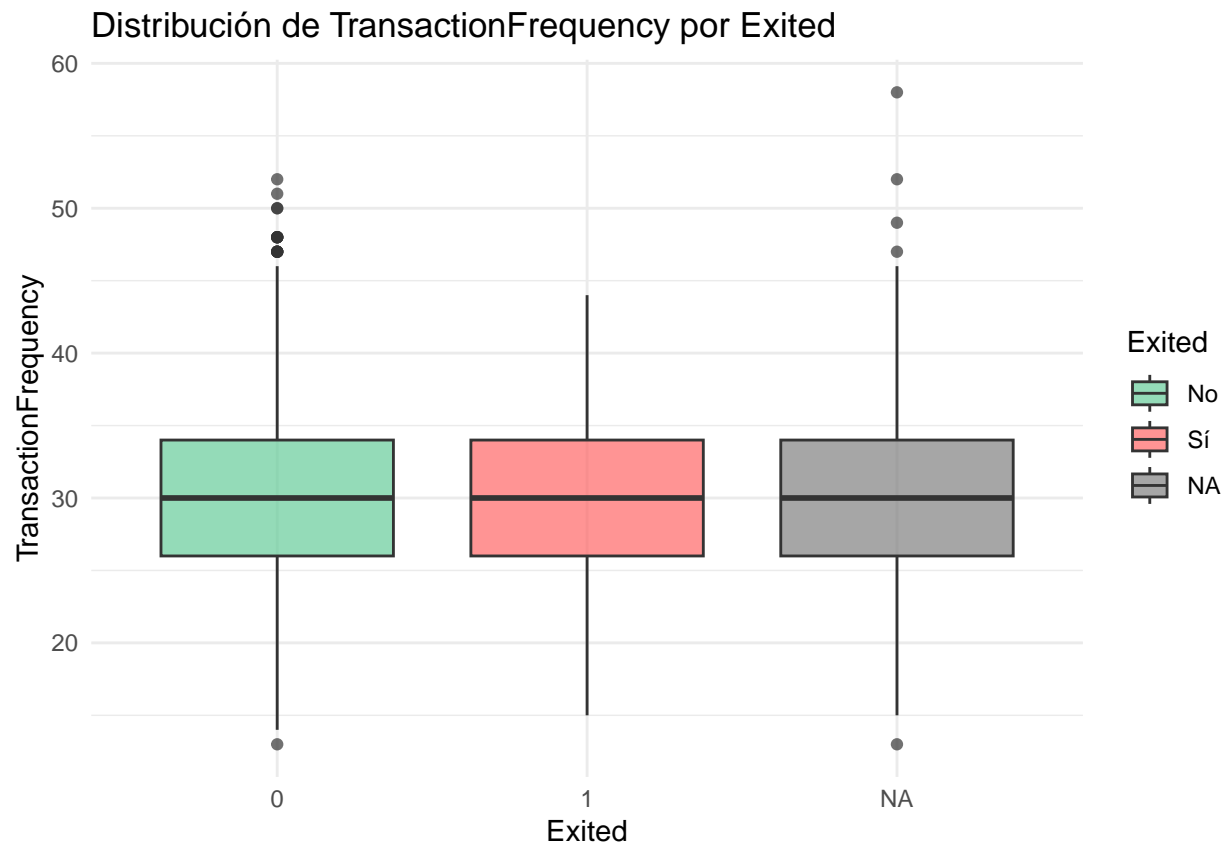


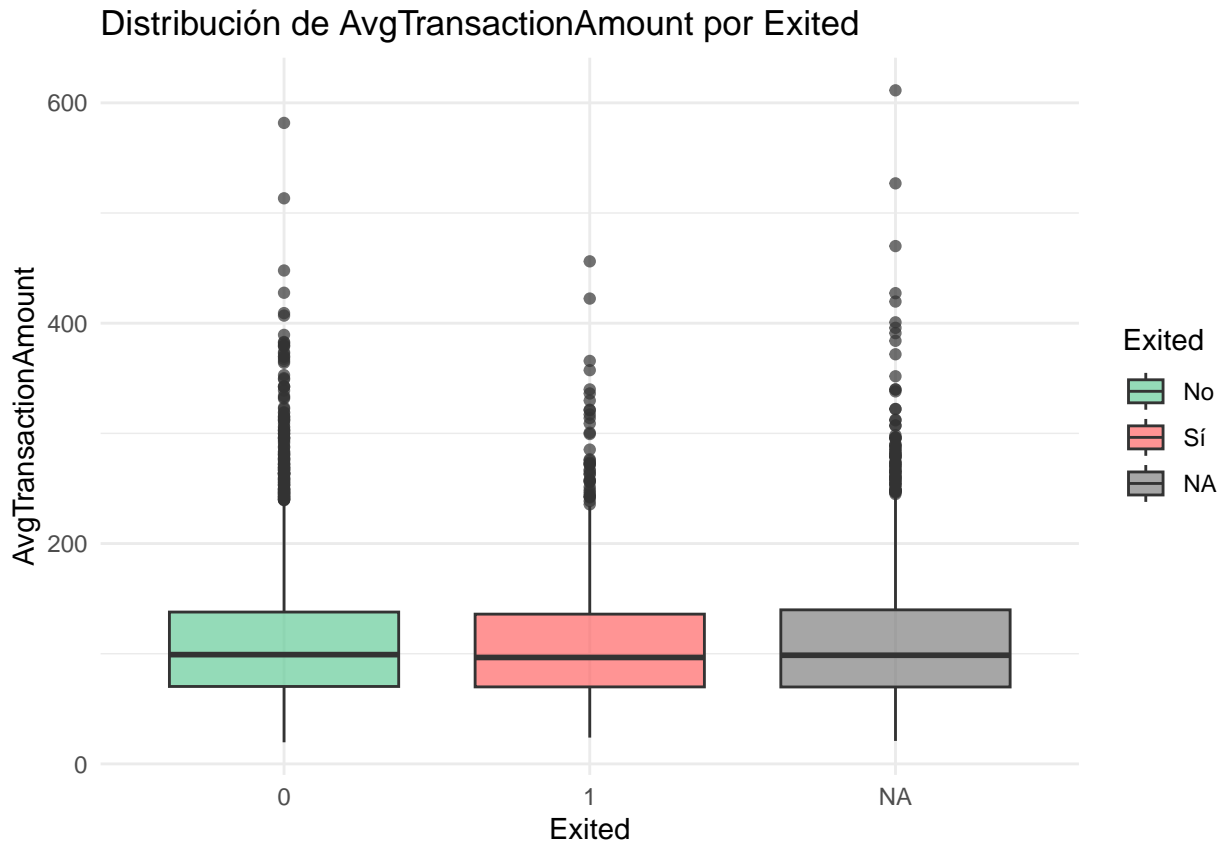


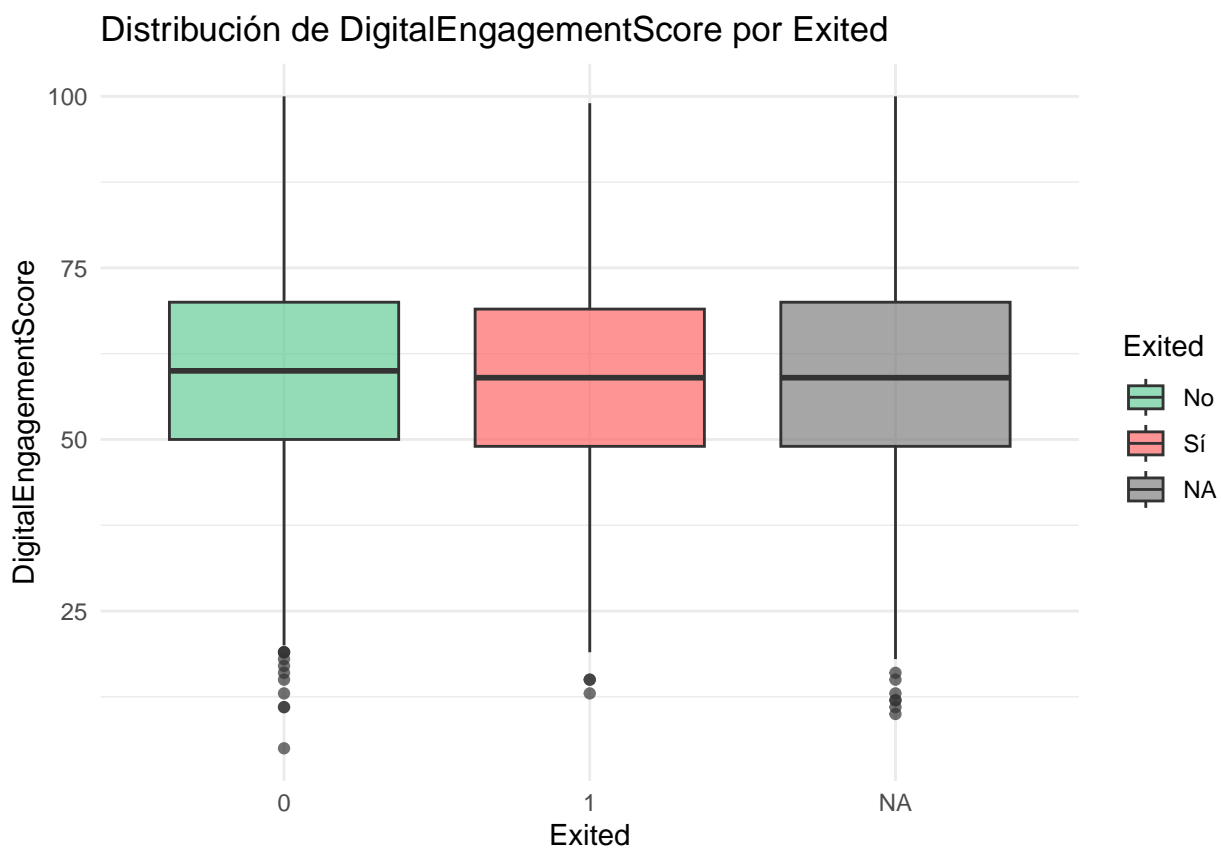


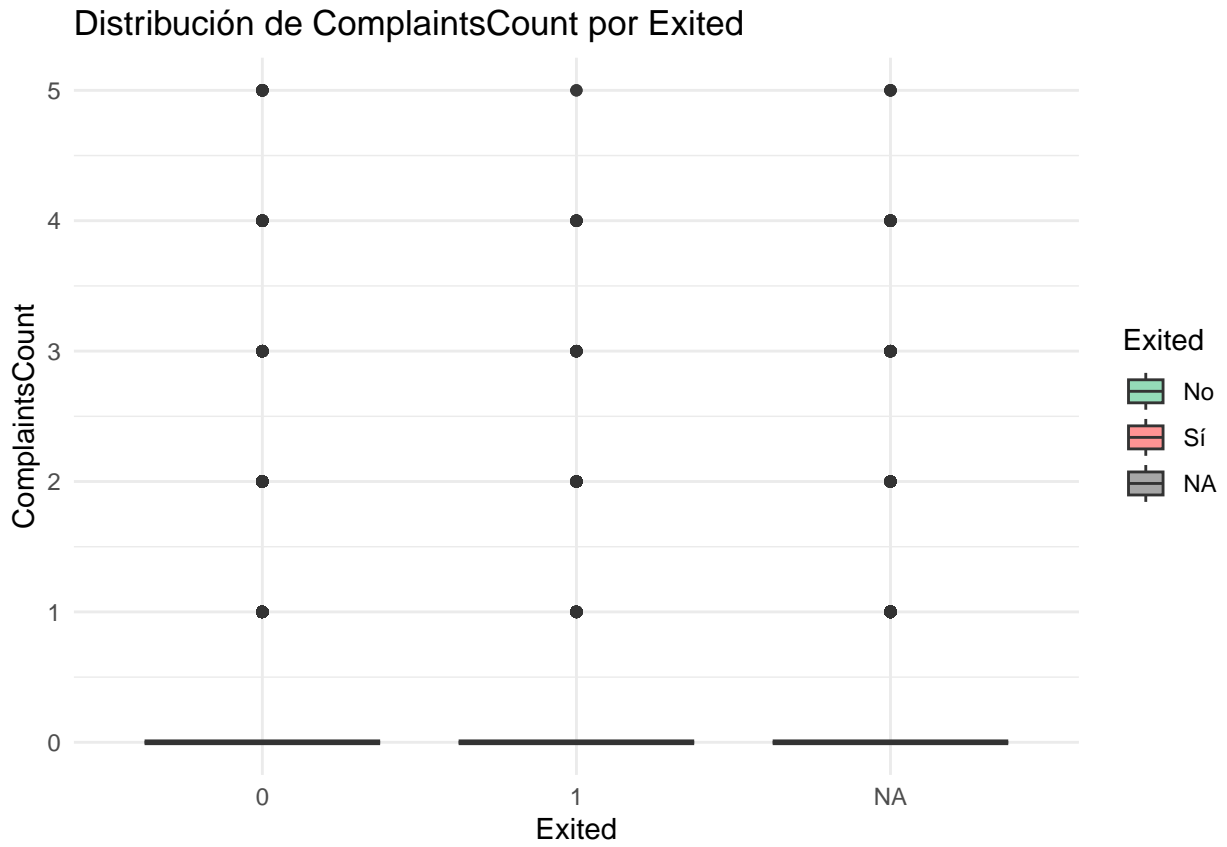


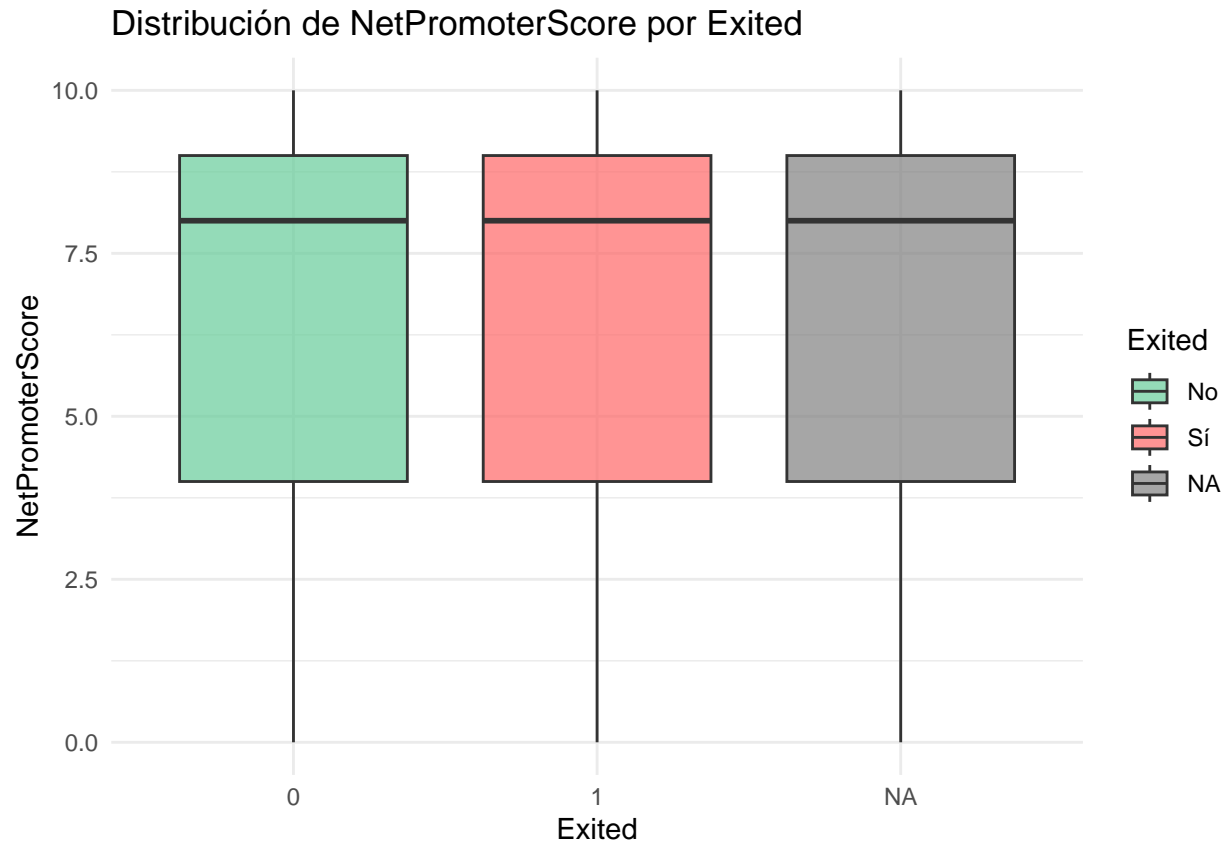












Observem la mateixa distribució de les variables numèriques segons si marxa o no del banc excepte les variables age, creditscore, numofproducts, Balance i Estimated salary.

Realitzem el test de medianas per veure si la diferencia és significativa.

```
resultados_mediana <- data.frame(
  Variable = character(),
  Mediana_Exit0 = numeric(),
  Mediana_Exit1 = numeric(),
  p_value = numeric(),
  stringsAsFactors = FALSE
)

for (var in varNum) {
  medianas <- tapply(data[[var]], data$Exited, median, na.rm = TRUE)
  p_val <- wilcox.test(data[[var]] ~ data$Exited)$p.value

  resultados_mediana <- rbind(resultados_mediana, data.frame(
    Variable = var,
    Mediana_Exit0 = medianas["0"],
    Mediana_Exit1 = medianas["1"],
    p_value = p_val
  ))
}
resultados_mediana
```

```
##          Variable Mediana_Exit0 Mediana_Exit1      p_value
```

## 0	Age	36.00000	45.00000	1.973454e-114
## 01	CreditScore	653.00000	644.00000	1.860831e-02
## 02	Tenure	5.00000	5.00000	3.200349e-01
## 03	EstimatedSalary	98602.46500	106188.38500	4.059852e-02
## 04	Balance	93052.50000	108844.05000	5.804964e-12
## 05	NumOfProducts	2.00000	1.00000	9.255184e-22
## 06	TransactionFrequency	30.00000	30.00000	5.593502e-01
## 07	AvgTransactionAmount	99.16118	96.60327	3.556860e-01
## 08	DigitalEngagementScore	60.00000	59.00000	2.513216e-01
## 09	ComplaintsCount	0.00000	0.00000	7.733715e-01
## 010	NetPromoterScore	8.00000	8.00000	9.145862e-01

Com a resultat s'observa que ens surt significatiu aquells variables mencionades anteriorment. LLavors podem conclureix lo següent:

- Els que tenen una edat més elevada tendeixen a marxar del banc amb més probabilitat.
- Els que tenen un creditScore baix tendeixen a marxar del banc amb més probabilitat.
- Els que tenen un salary estimat més elevat tendeixen a marxar del banc amb més probabilitat.
- Els que tenen només un producte tendeixen a marxar amb més probabilitat.
- Els que tenen un saldo més elevat tendeixen a marxar amb més probabilitat.

Missings

Annex

```
## ===== Geography vs. Gender =====
##
##           Female      Male
## France  0.4879249 0.5097015
## Germany 0.2629696 0.2402985
## Spain   0.2491055 0.2500000
## ===== Geography vs. MaritalStatus =====
##
##           Divorced  Married  Single  Widowed
## France  0.4829468 0.5075356 0.5131397 0.5387597
## Germany 0.2701228 0.2533605 0.2392808 0.2325581
## Spain   0.2469304 0.2391039 0.2475795 0.2286822
## ===== Geography vs. EducationLevel =====
##
##           High School  Other Postgraduate University
## France  0.5100473 0.5260870 0.4808959 0.5092135
## Germany 0.2446809 0.2304348 0.2463768 0.2471910
## Spain   0.2452719 0.2434783 0.2727273 0.2435955
## ===== Geography vs. HasCrCard =====
##
##           0      1
## France  0.4996521 0.5030303
## Germany 0.2498260 0.2502165
## Spain   0.2505219 0.2467532
## ===== Geography vs. SavingsAccountFlag =====
##
##           0      1
```

```

## France 0.4920260 0.5068836
## Germany 0.2510337 0.2537547
## Spain 0.2569403 0.2393617
## ===== Geography vs. LoanStatus =====
##
## Active loan Default risk No loan
## France 0.4921179 0.4923372 0.5020590
## Germany 0.2529130 0.2681992 0.2512011
## Spain 0.2549692 0.2394636 0.2467399
## ===== Geography vs. CustomerSegment =====
##
## Affluent High Net Worth Mass Market
## France 0.5058500 0.4902163 0.4925613
## Germany 0.2573985 0.2533471 0.2597507
## Spain 0.2367515 0.2564367 0.2476880
## ===== Geography vs. Exited =====
##
## 0 1
## France 0.5237850 0.4035608
## Germany 0.2172795 0.3827893
## Spain 0.2589355 0.2136499
## ===== Geography vs. group =====
##
## test train
## France 0.5128571 0.4989796
## Germany 0.2490476 0.2514286
## Spain 0.2380952 0.2495918
## ===== Geography vs. IsActiveMember =====
##
## 0 1
## France 0.5042194 0.5128205
## Germany 0.2552743 0.2370809
## Spain 0.2405063 0.2500986
## ===== Gender vs. Geography =====
##
## France Germany Spain
## Female 0.4440374 0.4772727 0.4539527
## Male 0.5559626 0.5227273 0.5460473
## ===== Gender vs. MaritalStatus =====
##
## Divorced Married Single Widowed
## Female 0.4534247 0.4524577 0.4758621 0.4440154
## Male 0.5465753 0.5475423 0.5241379 0.5559846
## ===== Gender vs. EducationLevel =====
##
## High School Other Postgraduate University
## Female 0.4752829 0.4110169 0.4403183 0.4562028
## Male 0.5247171 0.5889831 0.5596817 0.5437972
## ===== Gender vs. HasCrCard =====
##
## 0 1
## Female 0.4645341 0.4563700
## Male 0.5354659 0.5436300
## ===== Gender vs. SavingsAccountFlag =====

```

```

##
##           0           1
##   Female 0.4636038 0.4539228
##   Male   0.5363962 0.5460772
## ===== Gender vs. LoanStatus =====
##
##           Active loan Default risk   No loan
##   Female  0.4863350   0.4504854 0.4399864
##   Male    0.5136650   0.5495146 0.5600136
## ===== Gender vs. CustomerSegment =====
##
##           Affluent High Net Worth Mass Market
##   Female 0.4658856   0.4385417   0.4541101
##   Male  0.5341144   0.5614583   0.5458899
## ===== Gender vs. Exited =====
##
##           0           1
##   Female 0.4251559 0.5674905
##   Male   0.5748441 0.4325095
## ===== Gender vs. group =====
##
##           test      train
##   Female 0.4542857 0.4557143
##   Male   0.5457143 0.5442857
## ===== Gender vs. IsActiveMember =====
##
##           0           1
##   Female 0.4625850 0.4349009
##   Male   0.5374150 0.5650991
## ===== MaritalStatus vs. Geography =====
##
##           France   Germany   Spain
##   Divorced 0.14268440 0.16150082 0.15274262
##   Married  0.50221685 0.50734095 0.49535865
##   Single   0.29907295 0.28221860 0.30210970
##   Widowed  0.05602580 0.04893964 0.04978903
## ===== MaritalStatus vs. Gender =====
##
##           Female      Male
##   Divorced 0.14652501 0.14988730
##   Married  0.49712262 0.51051841
##   Single   0.30544489 0.28549962
##   Widowed  0.05090748 0.05409467
## ===== MaritalStatus vs. EducationLevel =====
##
##           High School   Other Postgraduate University
##   Divorced  0.0000000 0.0000000   1.0000000 0.0000000
##   Married   0.1352335 0.0000000   0.0000000 1.0000000
##   Single    0.8647665 0.0000000   0.0000000 0.0000000
##   Widowed   0.0000000 1.0000000   0.0000000 0.0000000
## ===== MaritalStatus vs. HasCrCard =====
##
##           0           1
##   Divorced 0.13969107 0.14577259

```

```

## Married 0.50839490 0.50991254
## Single 0.30020148 0.29533528
## Widowed 0.05171256 0.04897959
## ===== MaritalStatus vs. SavingsAccountFlag =====
##
##           0           1
## Divorced 0.4480480 0.0000000
## Married 0.0000000 0.7722256
## Single 0.4102102 0.2277744
## Widowed 0.1417417 0.0000000
## ===== MaritalStatus vs. LoanStatus =====
##
##           Active loan Default risk No loan
## Divorced 0.3251404 0.5183752 0.0000000
## Married 0.0000000 0.0000000 0.8298376
## Single 0.6748596 0.0000000 0.1701624
## Widowed 0.0000000 0.4816248 0.0000000
## ===== MaritalStatus vs. CustomerSegment =====
##
##           Affluent High Net Worth Mass Market
## Divorced 0.0000000 0.7645195 0.0000000
## Married 0.0000000 0.0000000 1.0000000
## Single 1.0000000 0.0000000 0.0000000
## Widowed 0.0000000 0.2354805 0.0000000
## ===== MaritalStatus vs. Exited =====
##
##           0           1
## Divorced 0.14506173 0.14525692
## Married 0.52006173 0.50988142
## Single 0.29089506 0.29249012
## Widowed 0.04398148 0.05237154
## ===== MaritalStatus vs. group =====
##
##           test      train
## Divorced 0.15142857 0.14510204
## Married 0.48142857 0.51795918
## Single 0.30809524 0.29122449
## Widowed 0.05904762 0.04571429
## ===== MaritalStatus vs. IsActiveMember =====
##
##           0           1
## Divorced 0.14123581 0.15461049
## Married 0.50861707 0.50834658
## Single 0.29340059 0.29451510
## Widowed 0.05674653 0.04252782
## ===== EducationLevel vs. Geography =====
##
##           France Germany Spain
## High School 0.34770346 0.34385382 0.34016393
## Other 0.04875101 0.04401993 0.04590164
## Postgraduate 0.14705882 0.15531561 0.16967213
## University 0.45648670 0.45681063 0.44426230
## ===== EducationLevel vs. Gender =====
##

```

```

##           Female      Male
## High School 0.35419441 0.33058161
## Other      0.04305371 0.05215760
## Postgraduate 0.14735908 0.15834897
## University 0.45539281 0.45891182
## ===== EducationLevel vs. MaritalStatus =====
##
##           Divorced   Married   Single   Widowed
## High School 0.00000000 0.09046653 1.00000000 0.00000000
## Other      0.00000000 0.00000000 0.00000000 1.00000000
## Postgraduate 1.00000000 0.00000000 0.00000000 0.00000000
## University 0.00000000 0.90953347 0.00000000 0.00000000
## ===== EducationLevel vs. HasCrCard =====
##
##           0          1
## High School 0.34556787 0.33936782
## Other      0.05263158 0.04655172
## Postgraduate 0.15235457 0.15057471
## University 0.44944598 0.46350575
## ===== EducationLevel vs. SavingsAccountFlag =====
##
##           0          1
## High School 0.4325280 0.2929956
## Other      0.1249263 0.0000000
## Postgraduate 0.4425457 0.0000000
## University 0.0000000 0.7070044
## ===== EducationLevel vs. LoanStatus =====
##
##           Active loan Default risk   No loan
## High School 0.6677943 0.0000000 0.2421875
## Other      0.0000000 0.4688129 0.0000000
## Postgraduate 0.3322057 0.5311871 0.0000000
## University 0.0000000 0.0000000 0.7578125
## ===== EducationLevel vs. CustomerSegment =====
##
##           Affluent High Net Worth Mass Market
## High School 1.00000000 0.00000000 0.09716599
## Other      0.00000000 0.22966014 0.00000000
## Postgraduate 0.00000000 0.77033986 0.00000000
## University 0.00000000 0.00000000 0.90283401
## ===== EducationLevel vs. Exited =====
##
##           0          1
## High School 0.34192708 0.32547170
## Other      0.04244792 0.05094340
## Postgraduate 0.15000000 0.15094340
## University 0.46562500 0.47264151
## ===== EducationLevel vs. group =====
##
##           test      train
## High School 0.35333333 0.33836735
## Other      0.05380952 0.04428571
## Postgraduate 0.15619048 0.15020408
## University 0.43666667 0.46714286

```

```

## ===== EducationLevel vs. IsActiveMember =====
##
##           0           1
##   High School  0.33192210 0.34816857
##   Other        0.05376799 0.04135486
##   Postgraduate 0.15283658 0.16069319
##   University   0.46147333 0.44978338
## ===== HasCrCard vs. Geography =====
##
##           France    Germany    Spain
##   0 0.2917513 0.2928222 0.2962963
##   1 0.7082487 0.7071778 0.7037037
## ===== HasCrCard vs. Gender =====
##
##           Female      Male
##   0 0.2986142 0.2917772
##   1 0.7013858 0.7082228
## ===== HasCrCard vs. MaritalStatus =====
##
##           Divorced   Married    Single   Widowed
##   0 0.2937853 0.3020750 0.3061644 0.3142857
##   1 0.7062147 0.6979250 0.6938356 0.6857143
## ===== HasCrCard vs. EducationLevel =====
##
##           High School    Other Postgraduate University
##   0 0.2970238 0.3193277 0.2956989 0.2869142
##   1 0.7029762 0.6806723 0.7043011 0.7130858
## ===== HasCrCard vs. SavingsAccountFlag =====
##
##           0           1
##   0 0.2991607 0.2965261
##   1 0.7008393 0.7034739
## ===== HasCrCard vs. LoanStatus =====
##
##           Active loan Default risk   No loan
##   0 0.2968641 0.3070866 0.2941975
##   1 0.7031359 0.6929134 0.7058025
## ===== HasCrCard vs. CustomerSegment =====
##
##           Affluent High Net Worth Mass Market
##   0 0.3102740 0.3072862 0.2893258
##   1 0.6897260 0.6927138 0.7106742
## ===== HasCrCard vs. Exited =====
##
##           0           1
##   0 0.2933264 0.3172147
##   1 0.7066736 0.6827853
## ===== HasCrCard vs. group =====
##
##           test      train
##   0 0.2952381 0.2983673
##   1 0.7047619 0.7016327
## ===== HasCrCard vs. IsActiveMember =====
##

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##          0          1
##  0 0.3015013 0.3013752
##  1 0.6984987 0.6986248
## ===== SavingsAccountFlag vs. Geography =====
##
##      France    Germany    Spain
##  0 0.3395842 0.3438511 0.3625000
##  1 0.6604158 0.6561489 0.6375000
## ===== SavingsAccountFlag vs. Gender =====
##
##      Female    Male
##  0 0.3476510 0.3388617
##  1 0.6523490 0.6611383
## ===== SavingsAccountFlag vs. MaritalStatus =====
##
##      Divorced    Married    Single    Widowed
##  0 1.0000000 0.0000000 0.4789621 1.0000000
##  1 0.0000000 1.0000000 0.5210379 0.0000000
## ===== SavingsAccountFlag vs. EducationLevel =====
##
##      High School    Other Postgraduate University
##  0  0.4392579 1.0000000 1.0000000 0.0000000
##  1  0.5607421 0.0000000 0.0000000 1.0000000
## ===== SavingsAccountFlag vs. HasCrCard =====
##
##          0          1
##  0 0.3429553 0.3401222
##  1 0.6570447 0.6598778
## ===== SavingsAccountFlag vs. LoanStatus =====
##
##      Active loan Default risk    No loan
##  0  0.8218157 1.0000000 0.0000000
##  1  0.1781843 0.0000000 1.0000000
## ===== SavingsAccountFlag vs. CustomerSegment =====
##
##      Affluent High Net Worth Mass Market
##  0 0.472067 1.000000 0.000000
##  1 0.527933 0.000000 1.000000
## ===== SavingsAccountFlag vs. Exited =====
##
##          0          1
##  0 0.3381481 0.3313783
##  1 0.6618519 0.6686217
## ===== SavingsAccountFlag vs. group =====
##
##      test    train
##  0 0.3566667 0.3367347
##  1 0.6433333 0.6632653
## ===== SavingsAccountFlag vs. IsActiveMember =====
##
##          0          1
##  0 0.3438023 0.3405342
##  1 0.6561977 0.6594658
## ===== LoanStatus vs. Geography =====

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##
##           France      Germany      Spain
##   Active loan  0.2945037 0.2973409 0.3059211
##   Default risk 0.1054143 0.1128122 0.1027961
##   No loan      0.6000820 0.5898469 0.5912829
## ===== LoanStatus vs. Gender =====
##
##           Female      Male
##   Active loan  0.3126126 0.2752535
##   Default risk 0.1045045 0.1062711
##   No loan      0.5828829 0.6184754
## ===== LoanStatus vs. MaritalStatus =====
##
##           Divorced   Married   Single   Widowed
##   Active loan  0.6333789 0.0000000 0.6564208 0.0000000
##   Default risk 0.3666211 0.0000000 0.0000000 1.0000000
##   No loan      0.0000000 1.0000000 0.3435792 0.0000000
## ===== LoanStatus vs. EducationLevel =====
##
##           High School   Other Postgraduate University
##   Active loan  0.5805882 0.0000000 0.6503311 0.0000000
##   Default risk 0.0000000 1.0000000 0.3496689 0.0000000
##   No loan      0.4194118 0.0000000 0.0000000 1.0000000
## ===== LoanStatus vs. HasCrCard =====
##
##           0      1
##   Active loan  0.2939959 0.2932287
##   Default risk 0.1076605 0.1022958
##   No loan      0.5983437 0.6044754
## ===== LoanStatus vs. SavingsAccountFlag =====
##
##           0      1
##   Active loan  0.7081144 0.0821875
##   Default risk 0.2918856 0.0000000
##   No loan      0.0000000 0.9178125
## ===== LoanStatus vs. CustomerSegment =====
##
##           Affluent High Net Worth Mass Market
##   Active loan  0.6473001 0.4893617 0.0000000
##   Default risk 0.0000000 0.5106383 0.0000000
##   No loan      0.3526999 0.0000000 1.0000000
## ===== LoanStatus vs. Exited =====
##
##           0      1
##   Active loan  0.2875448 0.2945892
##   Default risk 0.1002050 0.1012024
##   No loan      0.6122501 0.6042084
## ===== LoanStatus vs. group =====
##
##           test      train
##   Active loan  0.3090476 0.2889796
##   Default risk 0.1080952 0.1004082
##   No loan      0.5828571 0.6106122
## ===== LoanStatus vs. IsActiveMember =====

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##
##           0           1
## Active loan 0.2984823 0.2997199
## Default risk 0.0994941 0.1060424
## No loan      0.6020236 0.5942377
## ===== CustomerSegment vs. Geography =====
##
##           France   Germany   Spain
## Affluent      0.3017241 0.2954186 0.2845327
## High Net Worth 0.1954023 0.1943128 0.2059553
## Mass Market    0.5028736 0.5102686 0.5095120
## ===== CustomerSegment vs. Gender =====
##
##           Female   Male
## Affluent      0.3024609 0.2889635
## High Net Worth 0.1883669 0.2009694
## Mass Market    0.5091723 0.5100671
## ===== CustomerSegment vs. MaritalStatus =====
##
##           Divorced Married Single Widowed
## Affluent      0         0         1         0
## High Net Worth 1         0         0         1
## Mass Market    0         1         0         0
## ===== CustomerSegment vs. EducationLevel =====
##
##           High School   Other Postgraduate University
## Affluent      0.8570578 0.0000000 0.0000000 0.0000000
## High Net Worth 0.0000000 1.0000000 1.0000000 0.0000000
## Mass Market    0.1429422 0.0000000 0.0000000 1.0000000
## ===== CustomerSegment vs. HasCrCard =====
##
##           0           1
## Affluent      0.3092150 0.2932440
## High Net Worth 0.1986348 0.1910309
## Mass Market    0.4921502 0.5157251
## ===== CustomerSegment vs. SavingsAccountFlag =====
##
##           0           1
## Affluent      0.4119439 0.2308397
## High Net Worth 0.5880561 0.0000000
## Mass Market    0.0000000 0.7691603
## ===== CustomerSegment vs. LoanStatus =====
##
##           Active loan Default risk   No loan
## Affluent      0.6622378 0.0000000 0.1720000
## High Net Worth 0.3377622 1.0000000 0.0000000
## Mass Market    0.0000000 0.0000000 0.8280000
## ===== CustomerSegment vs. Exited =====
##
##           0           1
## Affluent      0.2876607 0.2930693
## High Net Worth 0.1863753 0.2049505
## Mass Market    0.5259640 0.5019802
## ===== CustomerSegment vs. group =====

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##
##          test      train
##  Affluent      0.3114286 0.2887755
##  High Net Worth 0.2061905 0.1902041
##  Mass Market    0.4823810 0.5210204
## ===== CustomerSegment vs. IsActiveMember =====
##
##          0          1
##  Affluent      0.2910416 0.3001949
##  High Net Worth 0.2018860 0.1925926
##  Mass Market    0.5070724 0.5072125
## ===== Exited vs. Geography =====
##
##      France  Germany  Spain
##  0 0.8331288 0.6858766 0.8233851
##  1 0.1668712 0.3141234 0.1766149
## ===== Exited vs. Gender =====
##
##      Female      Male
##  0 0.7326467 0.8293963
##  1 0.2673533 0.1706037
## ===== Exited vs. MaritalStatus =====
##
##      Divorced  Married  Single  Widowed
##  0 0.7932489 0.7966903 0.7925718 0.7633929
##  1 0.2067511 0.2033097 0.2074282 0.2366071
## ===== Exited vs. EducationLevel =====
##
##      High School  Other Postgraduate University
##  0  0.7919180 0.7511521  0.7826087  0.7811271
##  1  0.2080820 0.2488479  0.2173913  0.2188729
## ===== Exited vs. HasCrCard =====
##
##          0          1
##  0 0.7756498 0.7946481
##  1 0.2243502 0.2053519
## ===== Exited vs. SavingsAccountFlag =====
##
##          0          1
##  0 0.7945455 0.7895385
##  1 0.2054545 0.2104615
## ===== Exited vs. LoanStatus =====
##
##      Active loan Default risk  No loan
##  0  0.7923729  0.7947154 0.7984626
##  1  0.2076271  0.2052846 0.2015374
## ===== Exited vs. CustomerSegment =====
##
##      Affluent High Net Worth Mass Market
##  0 0.7908127  0.7778970  0.8014101
##  1 0.2091873  0.2221030  0.1985899
## ===== Exited vs. group =====
##
##      test      train

```

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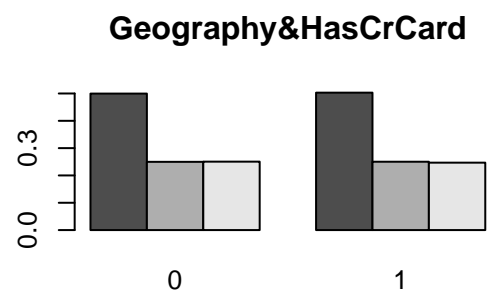
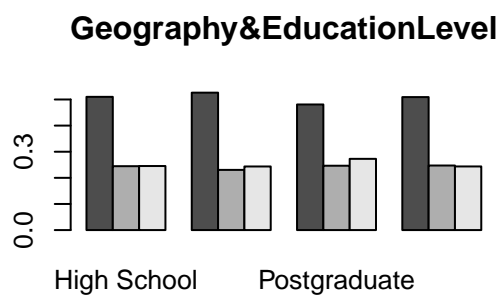
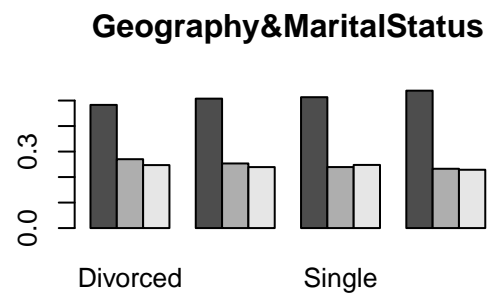
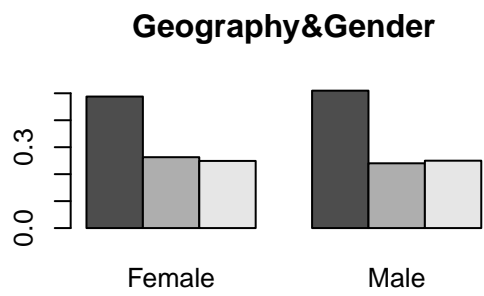
## 0      0.7928571
## 1      0.2071429
## ===== Exited vs. IsActiveMember =====
##
##          0          1
## 0 0.7297412 0.8537161
## 1 0.2702588 0.1462839
## ===== group vs. Geography =====
##
##          France    Germany    Spain
## test 0.3057922 0.2980057 0.2901915
## train 0.6942078 0.7019943 0.7098085
## ===== group vs. Gender =====
##
##          Female      Male
## test 0.2993411 0.3005507
## train 0.7006589 0.6994493
## ===== group vs. MaritalStatus =====
##
##          Divorced    Married    Single    Widowed
## test 0.3090379 0.2848690 0.3119576 0.3563218
## train 0.6909621 0.7151310 0.6880424 0.6436782
## ===== group vs. EducationLevel =====
##
##          High School    Other Postgraduate University
## test 0.3091667 0.3424242 0.3082707 0.2860262
## train 0.6908333 0.6575758 0.6917293 0.7139738
## ===== group vs. HasCrCard =====
##
##          0          1
## test 0.2977906 0.3009353
## train 0.7022094 0.6990647
## ===== group vs. SavingsAccountFlag =====
##
##          0          1
## test 0.3122134 0.2936318
## train 0.6877866 0.7063682
## ===== group vs. LoanStatus =====
##
##          Active loan Default risk    No loan
## test 0.3142857 0.3157163 0.2903226
## train 0.6857143 0.6842837 0.7096774
## ===== group vs. CustomerSegment =====
##
##          Affluent High Net Worth Mass Market
## test 0.3160947 0.3172161 0.2840718
## train 0.6839053 0.6827839 0.7159282
## ===== group vs. Exited =====
##
##          0 1
## test 0 0
## train 1 1
## ===== group vs. IsActiveMember =====
##

```

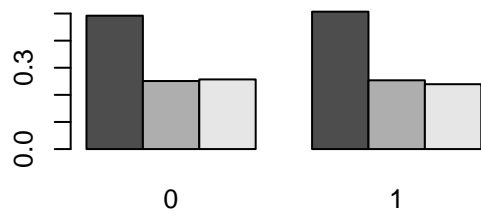
```

##          0          1
## test 0.3032811 0.2969312
## train 0.6967189 0.7030688
## ===== IsActiveMember vs. Geography =====
##
##      France      Germany      Spain
## 0 0.4789579 0.5016584 0.4734219
## 1 0.5210421 0.4983416 0.5265781
## ===== IsActiveMember vs. Gender =====
##
##      Female      Male
## 0 0.4929769 0.4650478
## 1 0.5070231 0.5349522
## ===== IsActiveMember vs. MaritalStatus =====
##
##      Divorced      Married      Single      Widowed
## 0 0.4634483 0.4861390 0.4850591 0.5578512
## 1 0.5365517 0.5138610 0.5149409 0.4421488
## ===== IsActiveMember vs. EducationLevel =====
##
##      High School      Other Postgraduate University
## 0 0.4700240 0.5474138 0.4694408 0.4883513
## 1 0.5299760 0.4525862 0.5305592 0.5116487
## ===== IsActiveMember vs. HasCrCard =====
##
##          0          1
## 0 0.4852349 0.4850854
## 1 0.5147651 0.5149146
## ===== IsActiveMember vs. SavingsAccountFlag =====
##
##          0          1
## 0 0.4863744 0.4827480
## 1 0.5136256 0.5172520
## ===== IsActiveMember vs. LoanStatus =====
##
##      Active loan Default risk      No loan
## 0 0.4859300 0.4710579 0.4902163
## 1 0.5140700 0.5289421 0.5097837
## ===== IsActiveMember vs. CustomerSegment =====
##
##      Affluent High Net Worth Mass Market
## 0 0.4685990 0.4880829 0.4762480
## 1 0.5314010 0.5119171 0.5237520
## ===== IsActiveMember vs. Exited =====
##
##          0          1
## 0 0.4420457 0.6313181
## 1 0.5579543 0.3686819
## ===== IsActiveMember vs. group =====
##
##      test      train
## 0 0.4885714 0.4810204
## 1 0.5114286 0.5189796

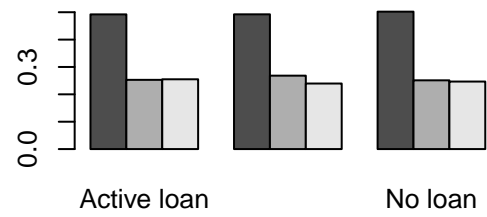
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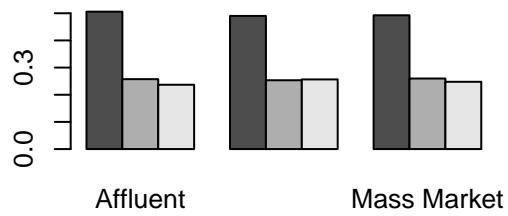
Geography&SavingsAccountFlag



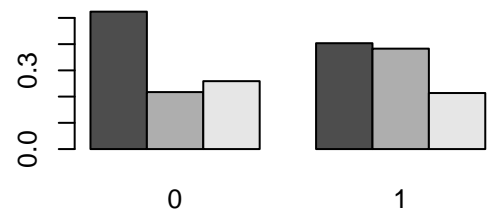
Geography&LoanStatus

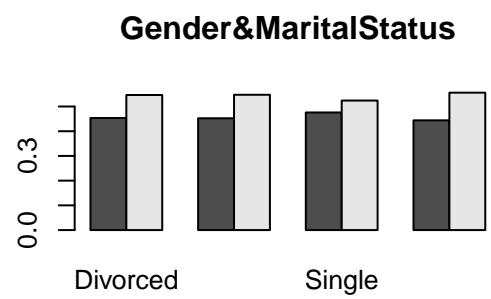
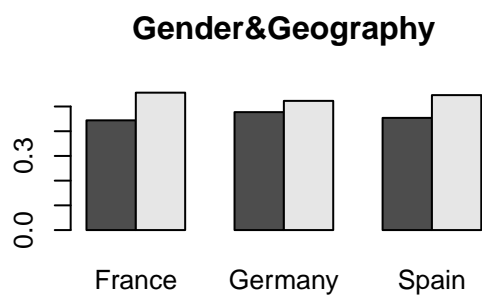
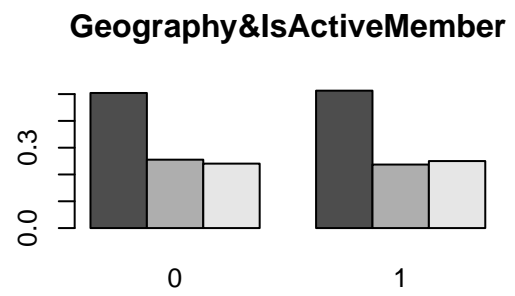
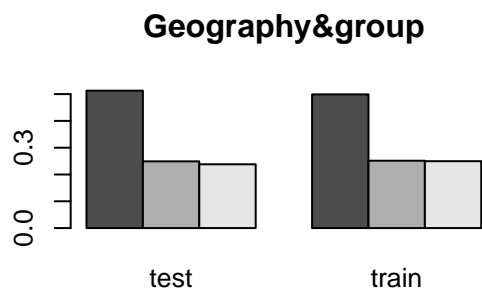


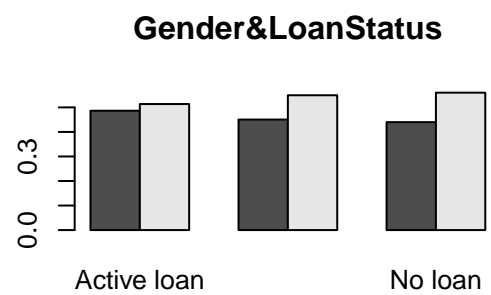
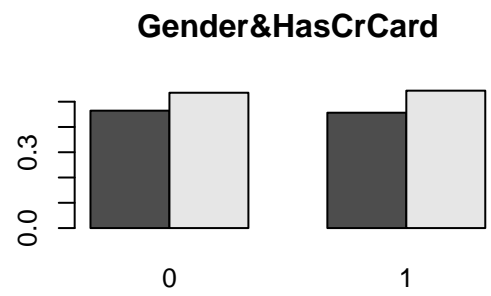
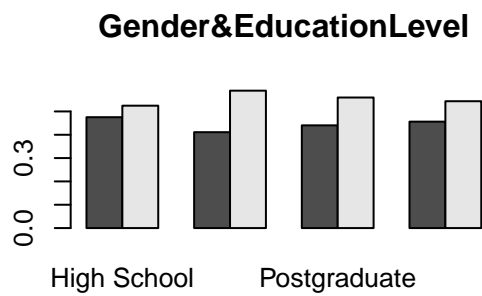
Geography&CustomerSegment

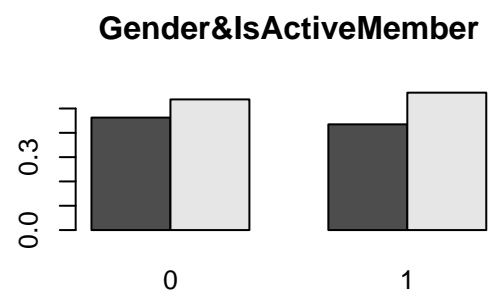
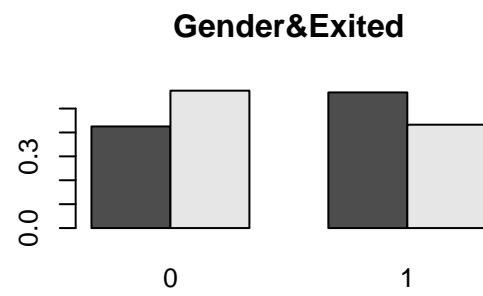
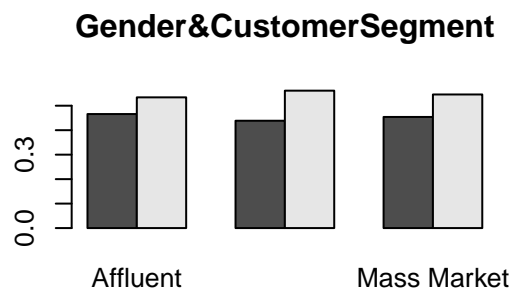


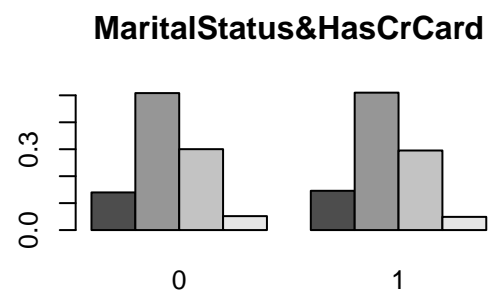
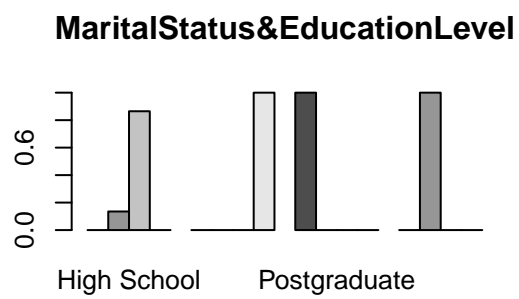
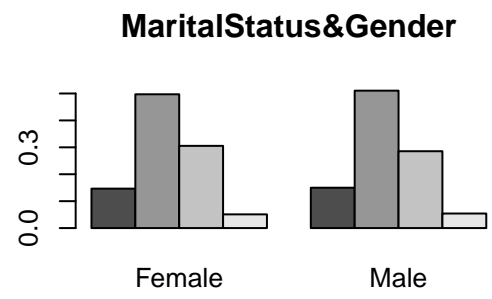
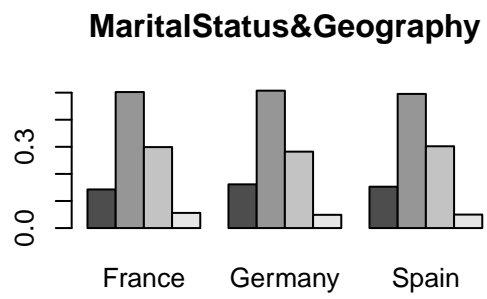
Geography&Exited



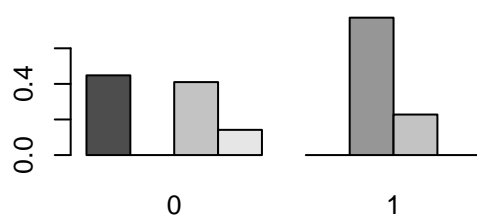




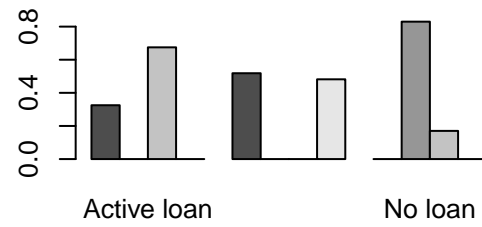




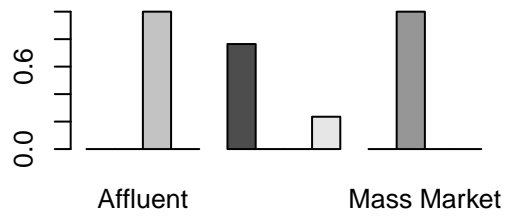
MaritalStatus&SavingsAccountFlag



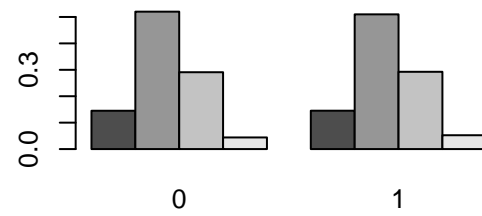
MaritalStatus&LoanStatus

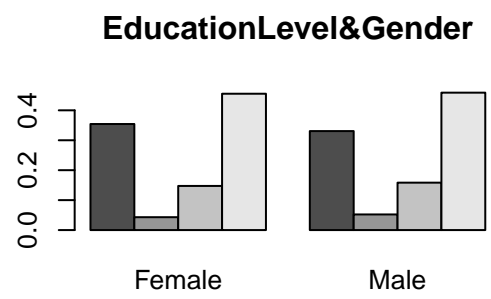
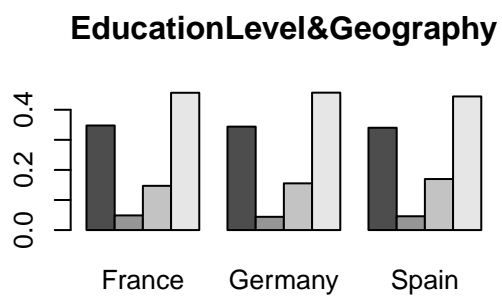
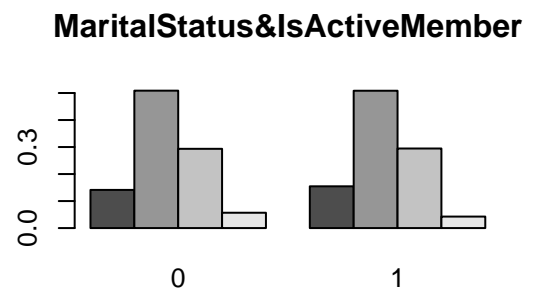
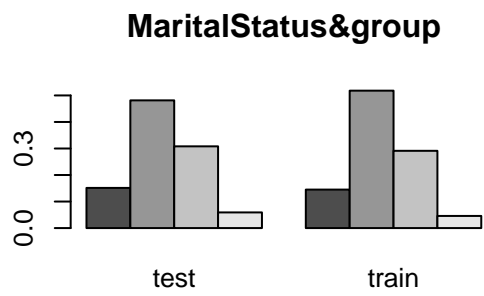


MaritalStatus&CustomerSegment

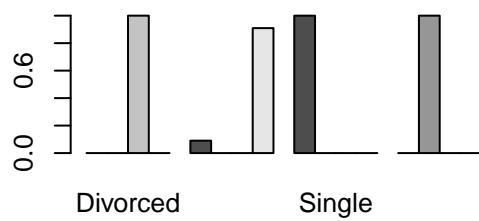


MaritalStatus&Exited

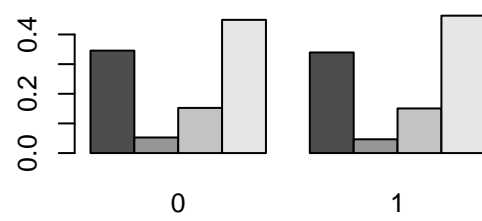




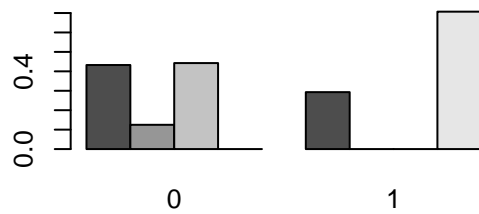
EducationLevel&MaritalStatus



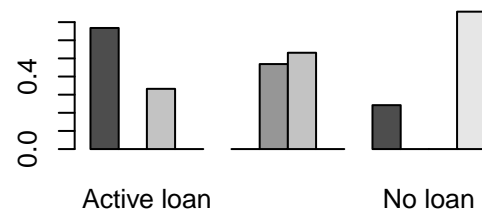
EducationLevel&HasCrCard



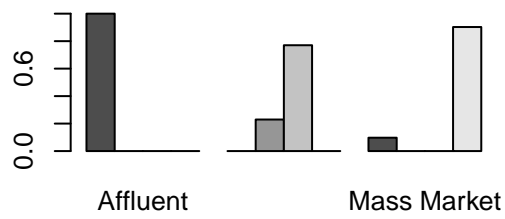
EducationLevel&SavingsAccountFlag



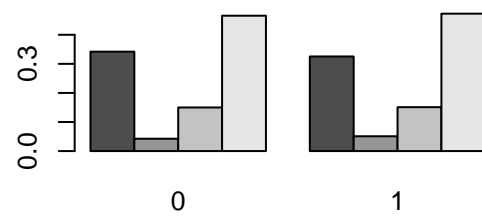
EducationLevel&LoanStatus



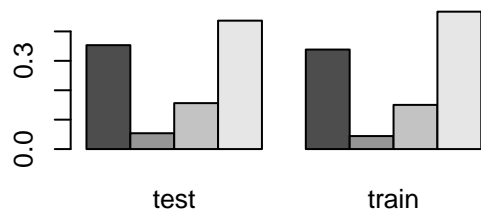
EducationLevel&CustomerSegment



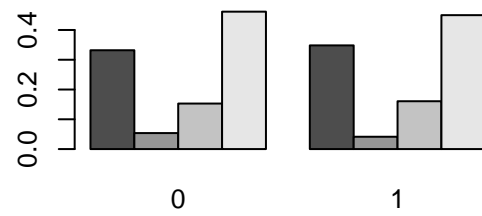
EducationLevel&Exited

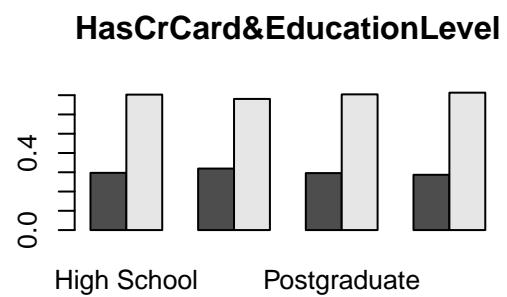
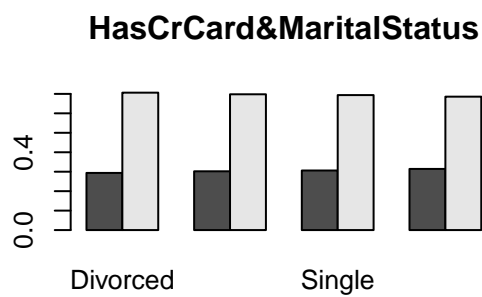
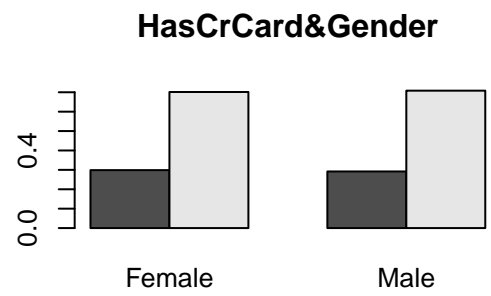
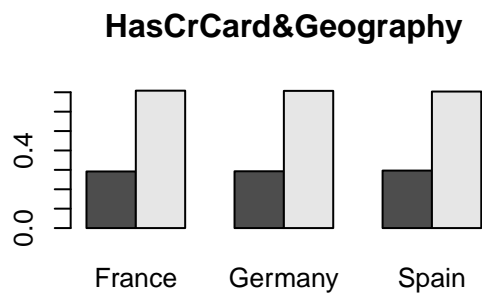


EducationLevel&group

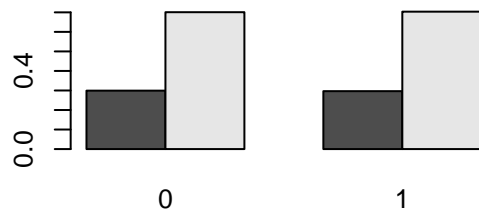


EducationLevel&IsActiveMember

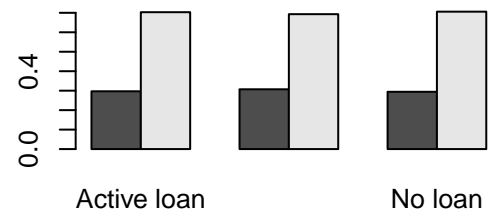




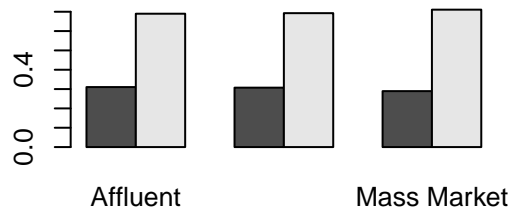
HasCrCard&SavingsAccountFlag



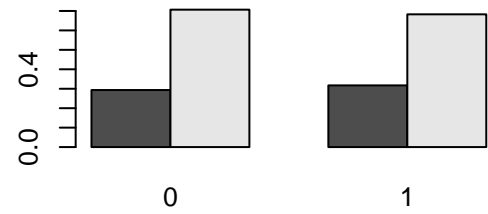
HasCrCard&LoanStatus

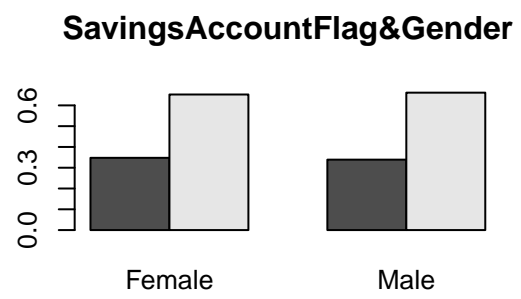
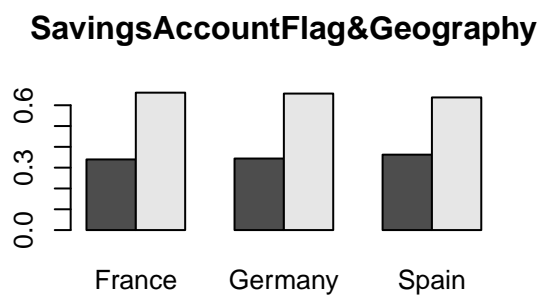
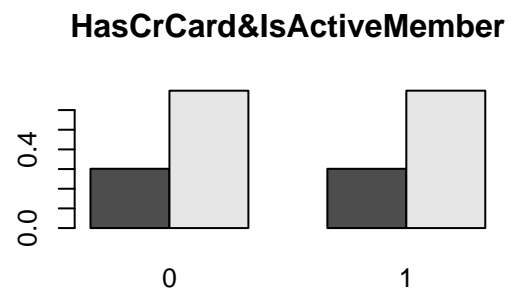
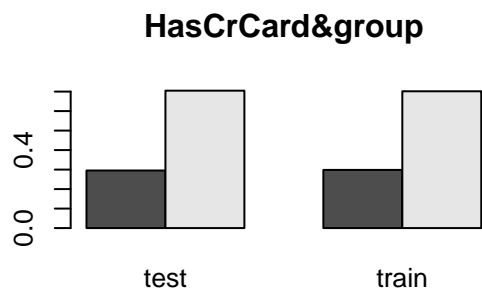


HasCrCard&CustomerSegment

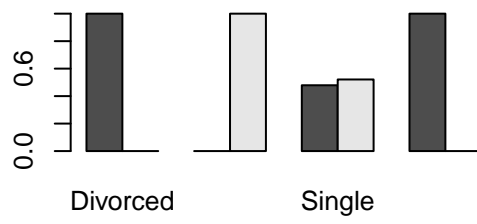


HasCrCard&Exited

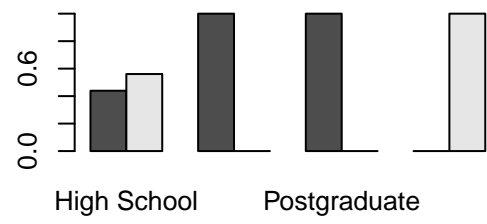




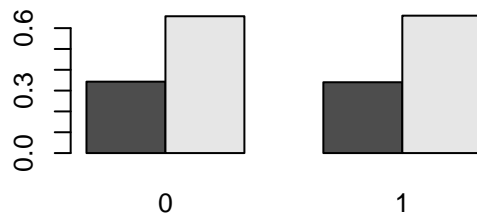
SavingsAccountFlag&MaritalStatus



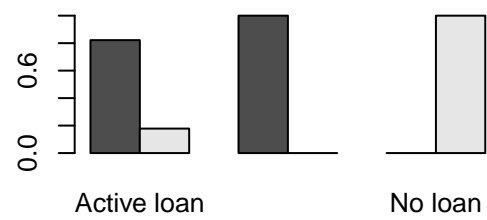
SavingsAccountFlag&EducationLeve



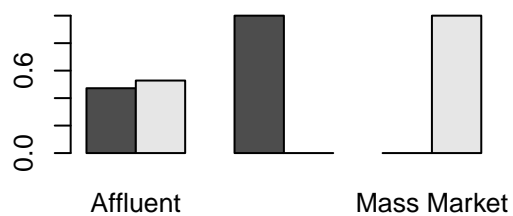
SavingsAccountFlag&HasCrCard



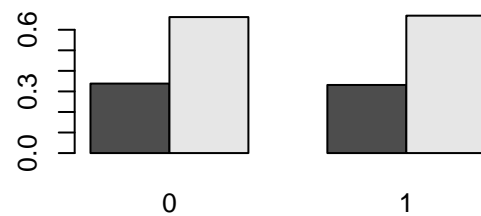
SavingsAccountFlag&LoanStatus



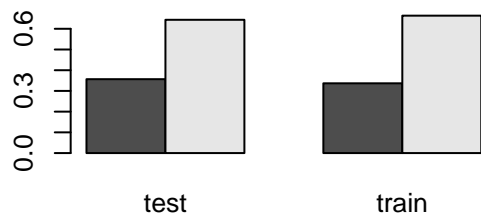
SavingsAccountFlag&CustomerSegme



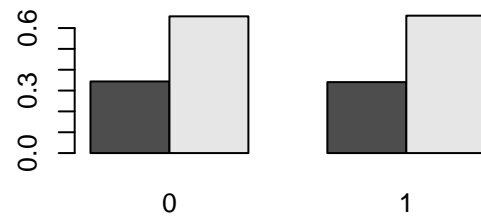
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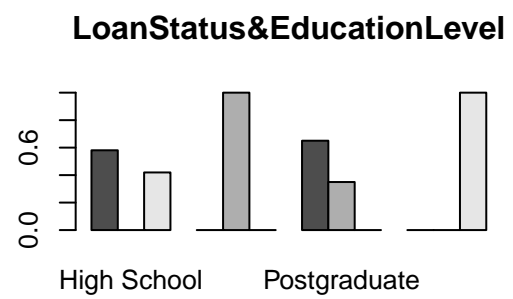
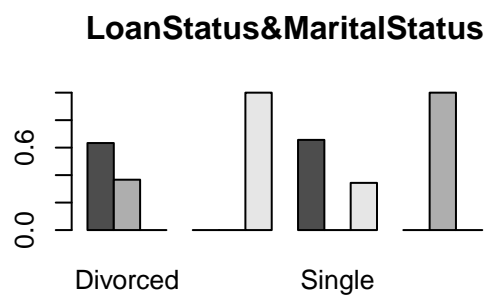
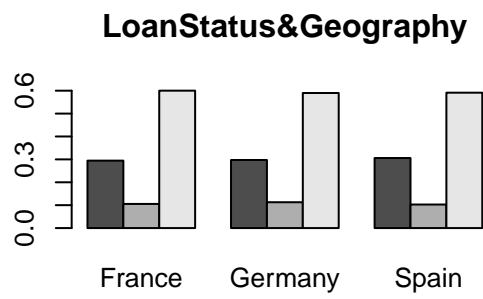


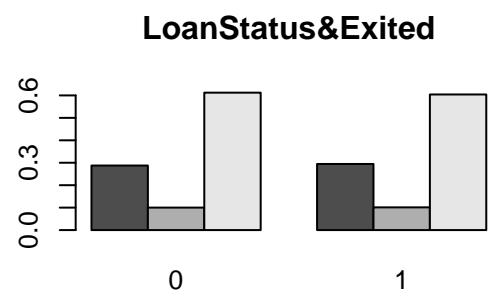
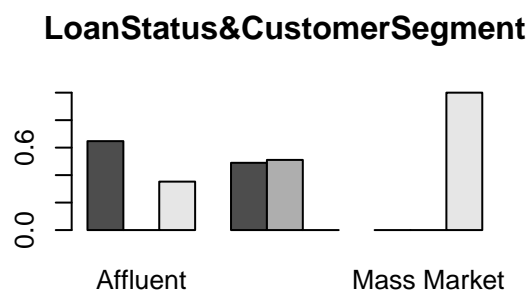
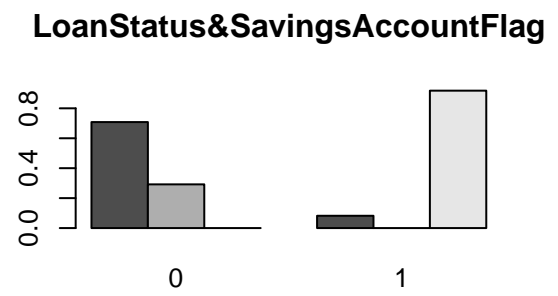
SavingsAccountFlag&group

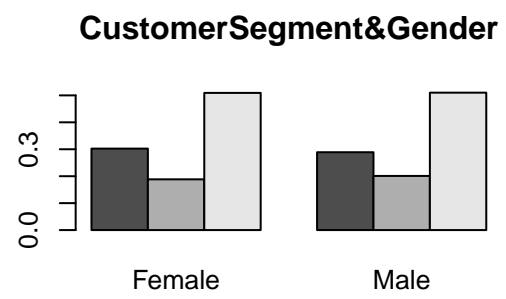
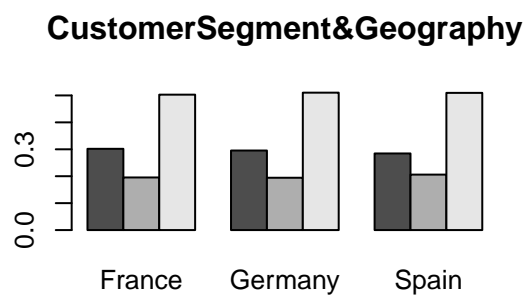
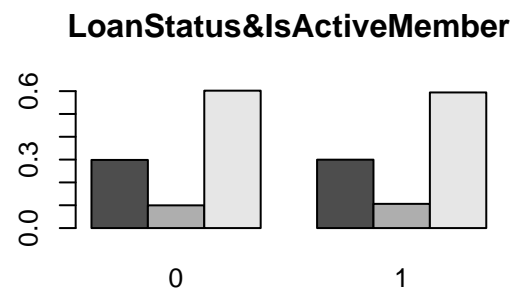


SavingsAccountFlag&IsActiveMembe

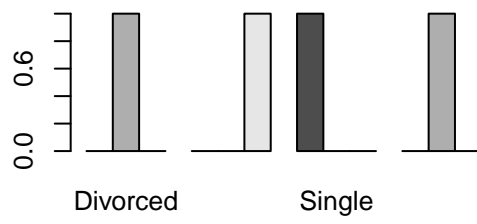




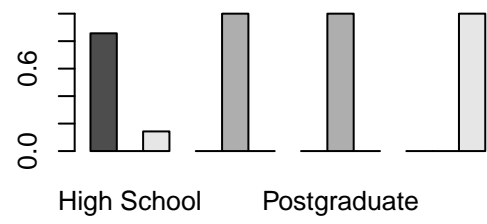




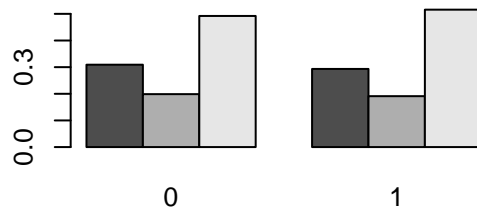
CustomerSegment&MaritalStatus



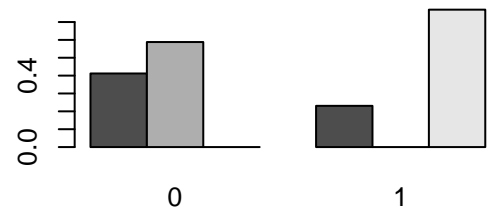
CustomerSegment&EducationLevel



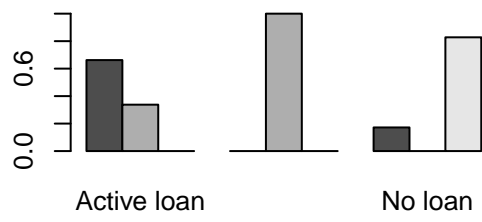
CustomerSegment&HasCrCard



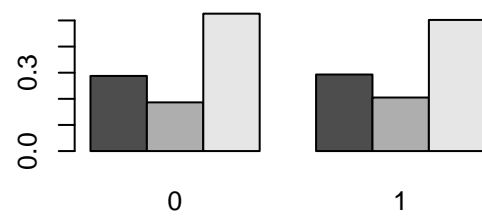
CustomerSegment&SavingsAccountFl:



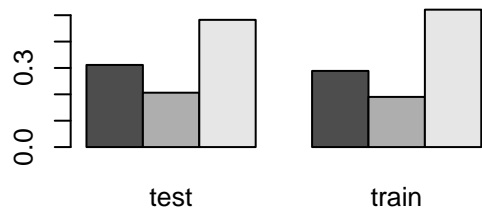
CustomerSegment&LoanStatus



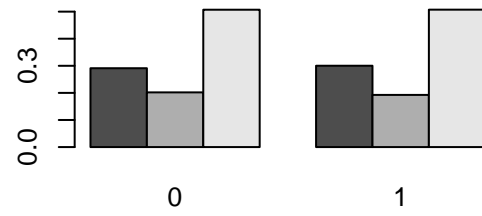
CustomerSegment&Exited

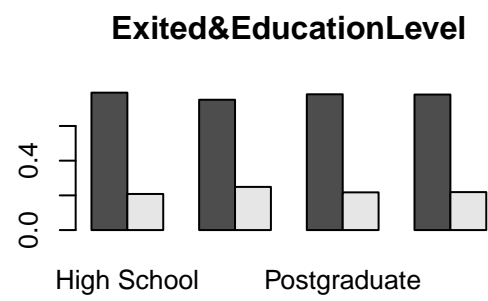
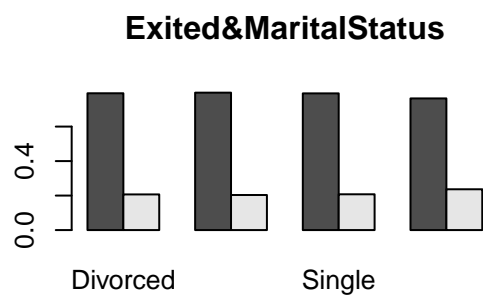
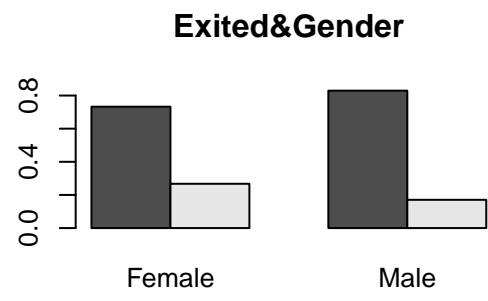
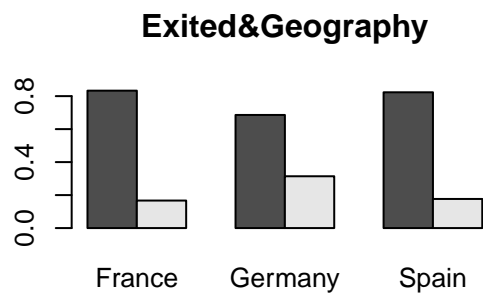


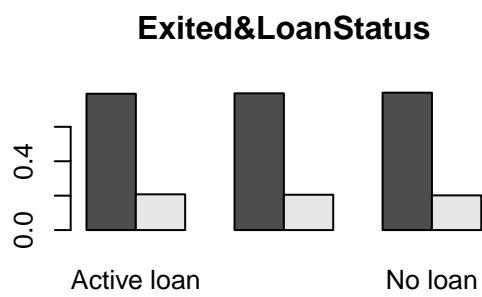
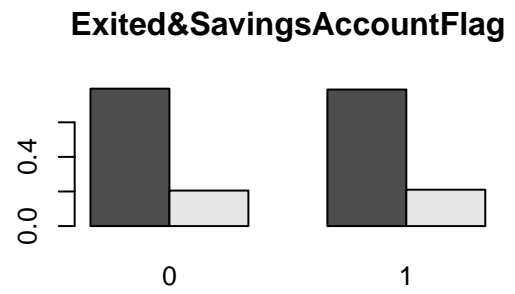
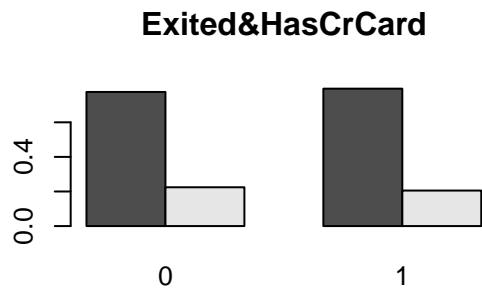
CustomerSegment&group

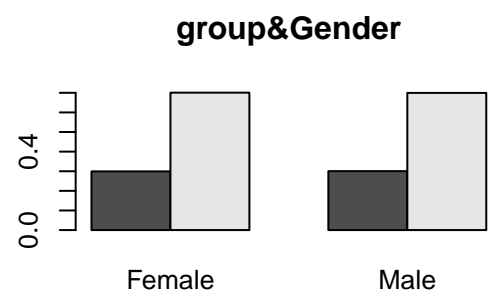
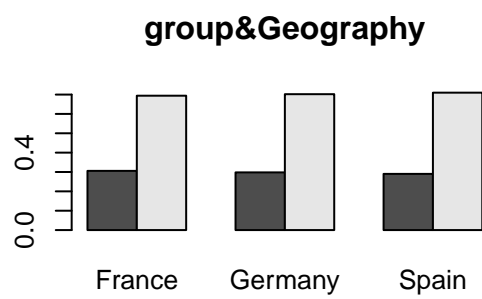
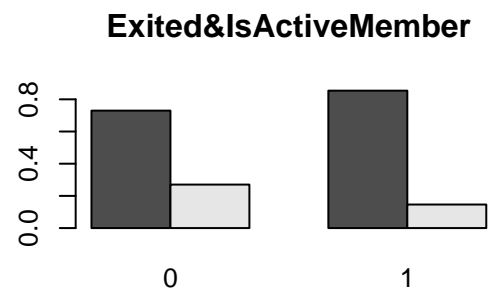


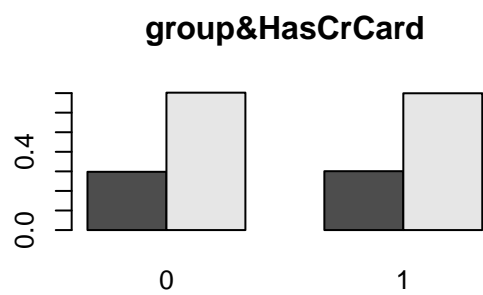
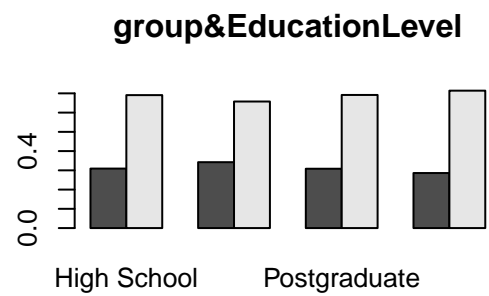
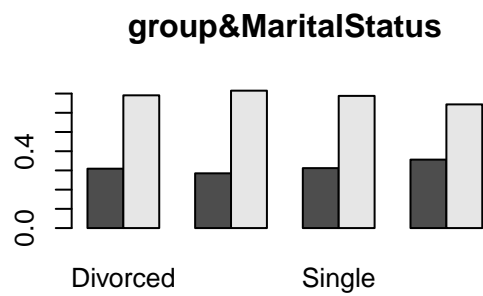
CustomerSegment&IsActiveMember

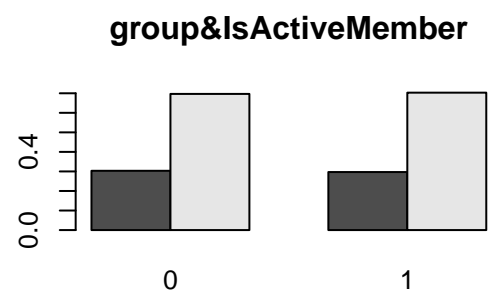
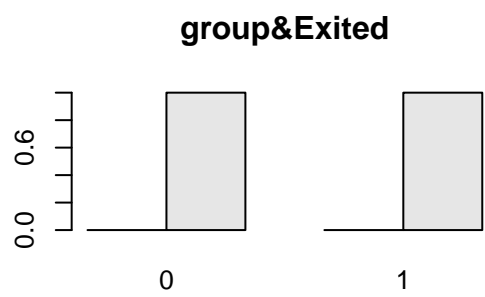
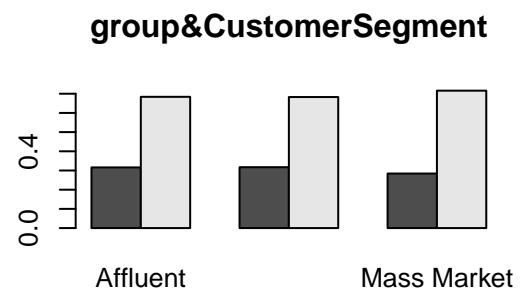
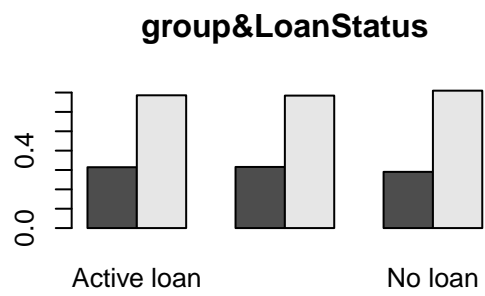




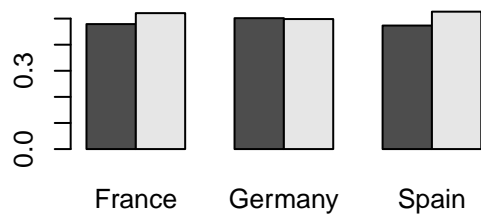




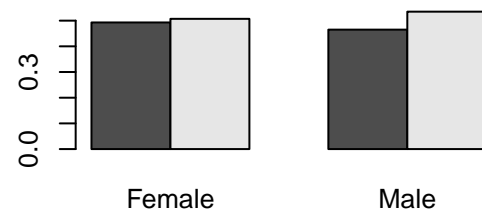




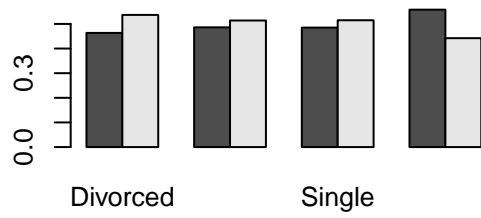
IsActiveMember&Geography



IsActiveMember&Gender



IsActiveMember&MaritalStatus



IsActiveMember&EducationLevel

