Desafio Meantrix

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Pré-processamento

Começamos carregando pacotes que iremos utilizar e importando os dados para pré-processamento.

```r
library(readr)
library(caret)
library(e1071)
library(ggplot2)
library(corrplot)
HR_Employee <- read_csv("HR-Employee.csv")
summary(HR_Employee)
```

```
##       Age         Attrition          BusinessTravel       DailyRate
##  Min.   :18.00   Length:1470        Length:1470        Min.   : 102.0
##  1st Qu.:30.00   Class :character   Class :character   1st Qu.: 465.0
##  Median :36.00   Mode  :character   Mode  :character   Median : 802.0
##  Mean   :36.92                                         Mean   : 802.5
##  3rd Qu.:43.00                                         3rd Qu.:1157.0
##  Max.   :60.00                                         Max.   :1499.0
##   Department         DistanceFromHome   Education     EducationField
##  Length:1470        Min.   : 1.000   Min.   :1.000   Length:1470
##  Class :character   1st Qu.: 2.000   1st Qu.:2.000   Class :character
##  Mode  :character   Median : 7.000   Median :3.000   Mode  :character
##                     Mean   : 9.193   Mean   :2.913
##                     3rd Qu.:14.000   3rd Qu.:4.000
##                     Max.   :29.000   Max.   :5.000
##  EmployeeCount EmployeeNumber   EnvironmentSatisfaction    Gender
##  Min.   :1     Min.   :   1.0   Min.   :1.000           Length:1470
##  1st Qu.:1     1st Qu.: 491.2   1st Qu.:2.000           Class :character
##  Median :1     Median :1020.5   Median :3.000           Mode  :character
##  Mean   :1     Mean   :1024.9   Mean   :2.722
##  3rd Qu.:1     3rd Qu.:1555.8   3rd Qu.:4.000
##  Max.   :1     Max.   :2068.0   Max.   :4.000
##    HourlyRate     JobInvolvement    JobLevel       JobRole
##  Min.   : 30.00   Min.   :1.00   Min.   :1.000   Length:1470
##  1st Qu.: 48.00   1st Qu.:2.00   1st Qu.:1.000   Class :character
##  Median : 66.00   Median :3.00   Median :2.000   Mode  :character
##  Mean   : 65.89   Mean   :2.73   Mean   :2.064
##  3rd Qu.: 83.75   3rd Qu.:3.00   3rd Qu.:3.000
##  Max.   :100.00   Max.   :4.00   Max.   :5.000
##  JobSatisfaction MaritalStatus      MonthlyIncome    MonthlyRate
##  Min.   :1.000   Length:1470        Min.   : 1009   Min.   : 2094
##  1st Qu.:2.000   Class :character   1st Qu.: 2911   1st Qu.: 8047
```

```
##  Median :3.000   Mode  :character   Median : 4919   Median :14236
##  Mean   :2.729                      Mean   : 6503   Mean   :14313
##  3rd Qu.:4.000                      3rd Qu.: 8379   3rd Qu.:20462
##  Max.   :4.000                      Max.   :19999   Max.   :26999
##  NumCompaniesWorked    Over18            OverTime         PercentSalaryHike
##  Min.   :0.000      Length:1470        Length:1470        Min.   :11.00
##  1st Qu.:1.000      Class :character   Class :character   1st Qu.:12.00
##  Median :2.000      Mode  :character   Mode  :character   Median :14.00
##  Mean   :2.693                                            Mean   :15.21
##  3rd Qu.:4.000                                            3rd Qu.:18.00
##  Max.   :9.000                                            Max.   :25.00
##  PerformanceRating RelationshipSatisfaction StandardHours StockOptionLevel
##  Min.   :3.000     Min.   :1.000            Min.   :80    Min.   :0.0000
##  1st Qu.:3.000     1st Qu.:2.000            1st Qu.:80    1st Qu.:0.0000
##  Median :3.000     Median :3.000            Median :80    Median :1.0000
##  Mean   :3.154     Mean   :2.712            Mean   :80    Mean   :0.7939
##  3rd Qu.:3.000     3rd Qu.:4.000            3rd Qu.:80    3rd Qu.:1.0000
##  Max.   :4.000     Max.   :4.000            Max.   :80    Max.   :3.0000
##  TotalWorkingYears TrainingTimesLastYear WorkLifeBalance YearsAtCompany
##  Min.   : 0.00     Min.   :0.000         Min.   :1.000   Min.   : 0.000
##  1st Qu.: 6.00     1st Qu.:2.000         1st Qu.:2.000   1st Qu.: 3.000
##  Median :10.00     Median :3.000         Median :3.000   Median : 5.000
##  Mean   :11.28     Mean   :2.799         Mean   :2.761   Mean   : 7.008
##  3rd Qu.:15.00     3rd Qu.:3.000         3rd Qu.:3.000   3rd Qu.: 9.000
##  Max.   :40.00     Max.   :6.000         Max.   :4.000   Max.   :40.000
##  YearsInCurrentRole YearsSinceLastPromotion YearsWithCurrManager
##  Min.   : 0.000     Min.   : 0.000          Min.   : 0.000
##  1st Qu.: 2.000     1st Qu.: 0.000          1st Qu.: 2.000
##  Median : 3.000     Median : 1.000          Median : 3.000
##  Mean   : 4.229     Mean   : 2.188          Mean   : 4.123
##  3rd Qu.: 7.000     3rd Qu.: 3.000          3rd Qu.: 7.000
##  Max.   :18.000     Max.   :15.000          Max.   :17.000
```

Codificação

Uma rápida inspeção revela que várias váriaveis independentes são categóricas e precisam ser codificadas para dummy variables. A função dummyVars do pacote caret ajuda a codificar rapidamente o dataframe, com exceção da variável Over18 que precisa ser codificada manualmente por ter apenas uma categoria.

```r
HR_Employee$Over18 <- ifelse(HR_Employee$Over18 == "Y", 1, 0)
```

Para codificar o restante evitando colinearidade perfeita, usamos dummyVars com fullRank = T.

```r
dmy <- dummyVars("~.", HR_Employee, fullRank=T)
enc_HR <- data.frame(predict(dmy, HR_Employee))
colnames(enc_HR)
```

```
##  [1] "Age"                              "AttritionYes"
##  [3] "BusinessTravelTravel_Frequently"  "BusinessTravelTravel_Rarely"
##  [5] "DailyRate"                        "DepartmentResearch...Development"
##  [7] "DepartmentSales"                  "DistanceFromHome"
##  [9] "Education"                        "EducationFieldLife.Sciences"
## [11] "EducationFieldMarketing"          "EducationFieldMedical"
## [13] "EducationFieldOther"              "EducationFieldTechnical.Degree"
## [15] "EmployeeCount"                    "EmployeeNumber"
## [17] "EnvironmentSatisfaction"          "GenderMale"
```

```
## [19] "HourlyRate"                     "JobInvolvement"
## [21] "JobLevel"                       "JobRoleHuman.Resources"
## [23] "JobRoleLaboratory.Technician"   "JobRoleManager"
## [25] "JobRoleManufacturing.Director"  "JobRoleResearch.Director"
## [27] "JobRoleResearch.Scientist"      "JobRoleSales.Executive"
## [29] "JobRoleSales.Representative"    "JobSatisfaction"
## [31] "MaritalStatusMarried"           "MaritalStatusSingle"
## [33] "MonthlyIncome"                  "MonthlyRate"
## [35] "NumCompaniesWorked"             "Over18"
## [37] "OverTimeYes"                    "PercentSalaryHike"
## [39] "PerformanceRating"              "RelationshipSatisfaction"
## [41] "StandardHours"                  "StockOptionLevel"
## [43] "TotalWorkingYears"              "TrainingTimesLastYear"
## [45] "WorkLifeBalance"                "YearsAtCompany"
## [47] "YearsInCurrentRole"             "YearsSinceLastPromotion"
## [49] "YearsWithCurrManager"
```

Variâncias próximas de zero

Com as variáveis categóricas codificadas, podemos identificar correlações entre variáveis independentes. Antes disso, no entanto, vamos utilizar a função nearZeroVar do pacote caret para identificar se, além da variável Over18, temos outras variáveis com apenas um valor único.

```
zeroVars <- nearZeroVar(enc_HR)
summary(enc_HR[zeroVars])
```

```
##  EmployeeCount JobRoleHuman.Resources     Over18  StandardHours
##  Min.   :1     Min.   :0.00000        Min.   :1   Min.   :80
##  1st Qu.:1     1st Qu.:0.00000        1st Qu.:1   1st Qu.:80
##  Median :1     Median :0.00000        Median :1   Median :80
##  Mean   :1     Mean   :0.03537        Mean   :1   Mean   :80
##  3rd Qu.:1     3rd Qu.:0.00000        3rd Qu.:1   3rd Qu.:80
##  Max.   :1     Max.   :1.00000        Max.   :1   Max.   :80
```

A função nearZeroVar identifica, de maneira geral, variáveis com variância próxima de zero (que portanto adicionam pouca ou nenhuma informação adicional ao modelo). Podemos ver acima que a variável JobRoleHuman.Resources, possui variância baixa, mas não nula. Vamos remover apenas as features constantes.

```
zeroVars <- zeroVars[-2]
enc_HR <- enc_HR[-zeroVars]
colnames(enc_HR)
```

```
##  [1] "Age"                            "AttritionYes"
##  [3] "BusinessTravelTravel_Frequently" "BusinessTravelTravel_Rarely"
##  [5] "DailyRate"                      "DepartmentResearch...Development"
##  [7] "DepartmentSales"                "DistanceFromHome"
##  [9] "Education"                      "EducationFieldLife.Sciences"
## [11] "EducationFieldMarketing"        "EducationFieldMedical"
## [13] "EducationFieldOther"            "EducationFieldTechnical.Degree"
## [15] "EmployeeNumber"                 "EnvironmentSatisfaction"
## [17] "GenderMale"                     "HourlyRate"
## [19] "JobInvolvement"                 "JobLevel"
## [21] "JobRoleHuman.Resources"         "JobRoleLaboratory.Technician"
## [23] "JobRoleManager"                 "JobRoleManufacturing.Director"
## [25] "JobRoleResearch.Director"       "JobRoleResearch.Scientist"
## [27] "JobRoleSales.Executive"         "JobRoleSales.Representative"
```

```
## [29] "JobSatisfaction"                  "MaritalStatusMarried"
## [31] "MaritalStatusSingle"              "MonthlyIncome"
## [33] "MonthlyRate"                      "NumCompaniesWorked"
## [35] "OverTimeYes"                      "PercentSalaryHike"
## [37] "PerformanceRating"                "RelationshipSatisfaction"
## [39] "StockOptionLevel"                 "TotalWorkingYears"
## [41] "TrainingTimesLastYear"            "WorkLifeBalance"
## [43] "YearsAtCompany"                   "YearsInCurrentRole"
## [45] "YearsSinceLastPromotion"          "YearsWithCurrManager"
```

Correlações

Podemos analisar correlações entre variáveis independentes e a variável AttritionYes.

```r
correlations <- cor(enc_HR)
correlations["AttritionYes",]
```

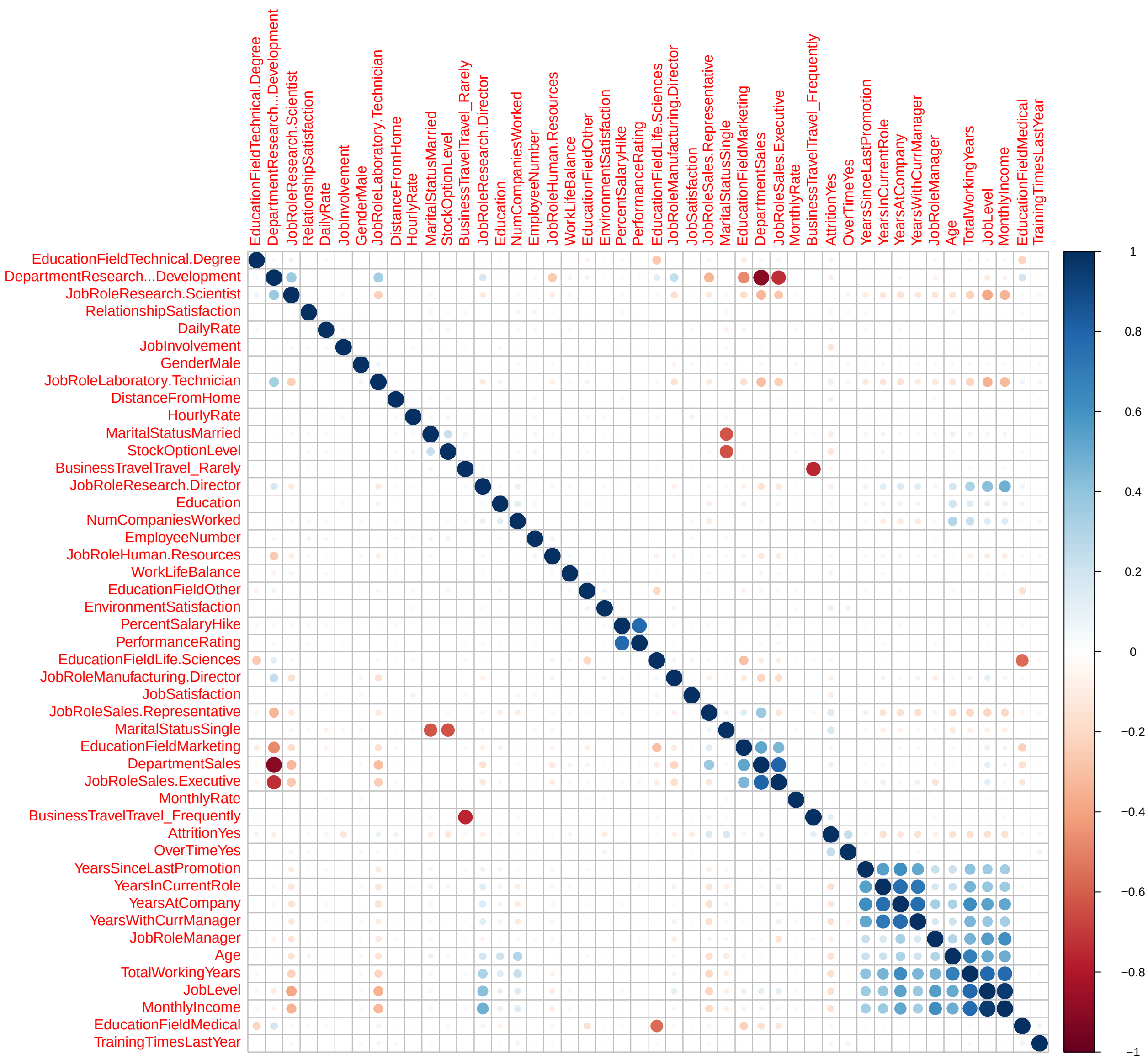
```
##                               Age                      AttritionYes
##                     -0.1592050069                      1.0000000000
##  BusinessTravelTravel_Frequently       BusinessTravelTravel_Rarely
##                      0.1151427655                     -0.0495378384
##                         DailyRate DepartmentResearch...Development
##                     -0.0566519919                     -0.0852929276
##                   DepartmentSales                  DistanceFromHome
##                      0.0808552021                      0.0779235830
##                         Education         EducationFieldLife.Sciences
##                     -0.0313728196                     -0.0327031477
##          EducationFieldMarketing             EducationFieldMedical
##                      0.0557806657                     -0.0469987159
##              EducationFieldOther   EducationFieldTechnical.Degree
##                     -0.0178975168                      0.0693545948
##                    EmployeeNumber           EnvironmentSatisfaction
##                     -0.0105772428                     -0.1033689783
##                        GenderMale                        HourlyRate
##                      0.0294532532                     -0.0068455496
##                    JobInvolvement                          JobLevel
##                     -0.1300159568                     -0.1691047509
##            JobRoleHuman.Resources     JobRoleLaboratory.Technician
##                      0.0362150821                      0.0982904855
##                    JobRoleManager    JobRoleManufacturing.Director
##                     -0.0833163842                     -0.0829939241
##          JobRoleResearch.Director        JobRoleResearch.Scientist
##                     -0.0888698417                     -0.0003595713
##            JobRoleSales.Executive      JobRoleSales.Representative
##                      0.0197743685                      0.1572342701
##                   JobSatisfaction              MaritalStatusMarried
##                     -0.1034811261                     -0.0909836512
##               MaritalStatusSingle                     MonthlyIncome
##                      0.1754185536                     -0.1598395824
##                       MonthlyRate                NumCompaniesWorked
##                      0.0151702125                      0.0434937391
##                       OverTimeYes                 PercentSalaryHike
##                      0.2461179942                     -0.0134782021
##                 PerformanceRating          RelationshipSatisfaction
##                      0.0028887517                     -0.0458722789
```

```
##             StockOptionLevel               TotalWorkingYears
##                -0.1371449189                   -0.1710632461
##        TrainingTimesLastYear                 WorkLifeBalance
##                -0.0594777986                   -0.0639390472
##               YearsAtCompany              YearsInCurrentRole
##                -0.1343922140                   -0.1605450043
##      YearsSinceLastPromotion            YearsWithCurrManager
##                -0.0330187751                   -0.1561993159
```

Nenhuma correlação se sobressai além da correlação da variável com ela mesma. Muitas variáveis parecem contribuir em alguma medida para a variação em AttritionYes, com a variável OverTimeYes tendo a maior correlação.

Podemos também plotar clusters de variáveis correlacionadas utilizando o pacote corrplot. Exportamos para png para melhor visualização.

```
corrMatrix <- corrplot(correlations, order="hclust", tl.cex=1)
```



```r
png("corrplot.png", width=1920, height=1080, units="px")
```

Identificamos correlações esperadas entre variáveis que indicam o tempo corrido desde algum evento (anos na companhia, anos desde a última promoção, etc). Correlações entre idade, tempo no mercado de trabalho e salário mensal também não são inesperadas. Caso tais correlações venham a ser problemáticas, ou caso queiramos experimentar com o modelo, podemos aplicar Principal Component Analysis para gerar features independentes entre si. No momento seguiremos com as features como estão.

Assimetria

Para verificar se temos features com distribuições assimétricas, utilizamos a função skewness do pacote e1071.

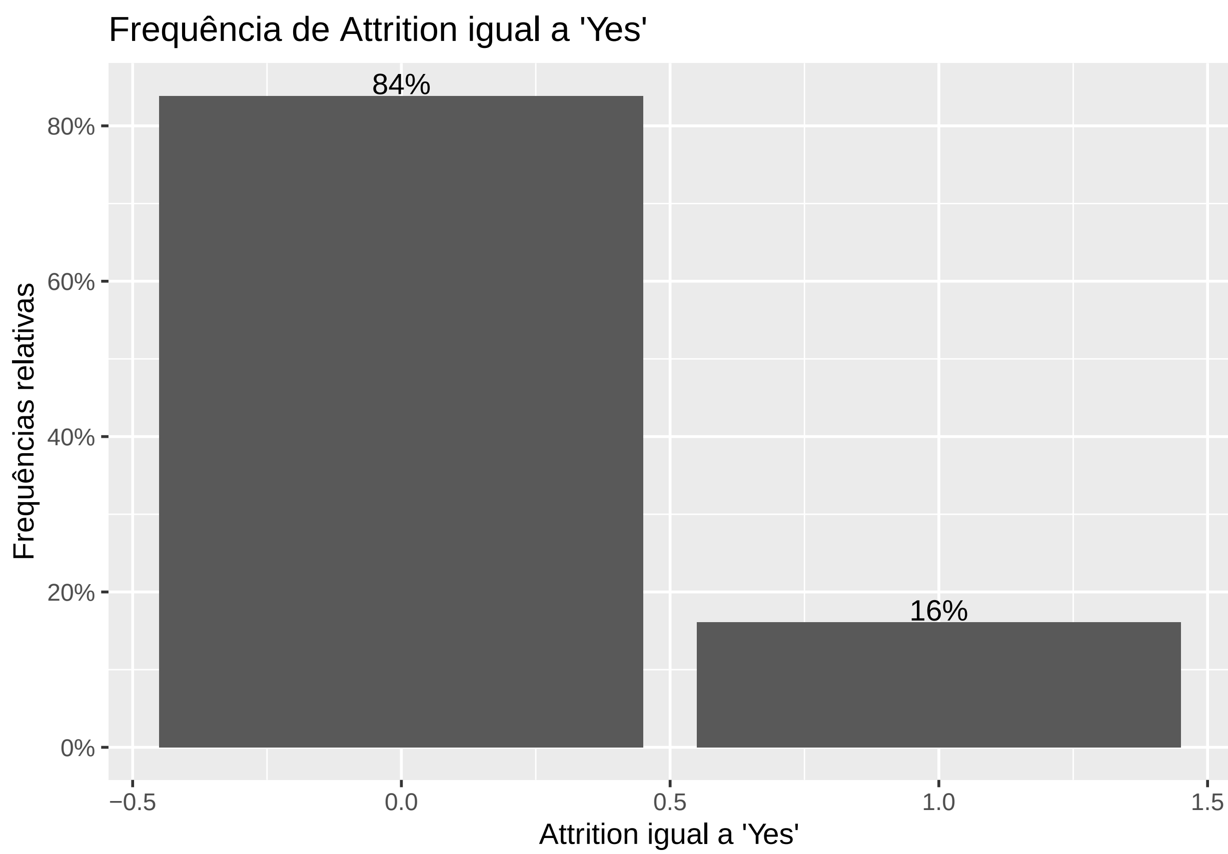
```r
skewValues <- apply(enc_HR, 2, skewness)
skewValues
```

```
##                               Age                       AttritionYes
##                       0.412443243                        1.840603819
##  BusinessTravelTravel_Frequently      BusinessTravelTravel_Rarely
##                       1.591813043                       -0.922106985
##                         DailyRate DepartmentResearch...Development
##                      -0.003511391                       -0.645616381
##                   DepartmentSales                   DistanceFromHome
##                       0.854411573                        0.956163540
##                         Education      EducationFieldLife.Sciences
##                      -0.289090164                        0.356191223
##           EducationFieldMarketing             EducationFieldMedical
##                       2.520630939                        0.792497676
##               EducationFieldOther   EducationFieldTechnical.Degree
##                       3.867214035                        2.866744428
##                    EmployeeNumber          EnvironmentSatisfaction
##                       0.016540210                       -0.320998308
##                        GenderMale                         HourlyRate
##                      -0.407831781                       -0.032245042
##                    JobInvolvement                           JobLevel
##                      -0.497402643                        1.023309576
##             JobRoleHuman.Resources     JobRoleLaboratory.Technician
##                       5.025364918                        1.698132940
##                    JobRoleManager    JobRoleManufacturing.Director
##                       3.385690560                        2.689346485
##           JobRoleResearch.Director        JobRoleResearch.Scientist
##                       3.924421023                        1.509128923
##             JobRoleSales.Executive      JobRoleSales.Representative
##                       1.338098805                        3.839343825
##                   JobSatisfaction              MaritalStatusMarried
##                      -0.328999464                        0.169138192
##               MaritalStatusSingle                      MonthlyIncome
##                       0.772295727                        1.367022404
##                       MonthlyRate                 NumCompaniesWorked
##                       0.018539911                        1.024377223
##                       OverTimeYes                  PercentSalaryHike
##                       0.962521412                        0.819452964
##                 PerformanceRating          RelationshipSatisfaction
##                       1.917962271                       -0.302209830
##                  StockOptionLevel                  TotalWorkingYears
##                       0.967003703                        1.114892944
```

```
##           TrainingTimesLastYear                  WorkLifeBalance
##                     0.551995858                     -0.551353300
##                  YearsAtCompany                YearsInCurrentRole
##                     1.760930007                      0.915491836
##         YearsSinceLastPromotion              YearsWithCurrManager
##                     1.980242248                      0.831750843
```

AttritionYes, que codifica Attrition, nossa variável target, é uma das variáveis que apresenta assimetria. Plotamos sua frequência relativa para inspeção visual.

```
ggplot(enc_HR, aes(x = AttritionYes)) +
  geom_bar(aes(y = (..count..)/sum(..count..))) +
  scale_y_continuous(labels = scales::percent) +
  geom_text(aes(label= scales::percent(..prop..), y=..prop..), stat="count", vjust = -.075) +
  xlab("Attrition igual a 'Yes'") +
  ylab("Frequências relativas") +
  ggtitle("Frequência de Attrition igual a 'Yes'")
```



Fica evidente que Attrition é igual a "Yes" (ou AttritionYes == 1) em apenas 16% da população. Um algoritmo que estimasse Attrition = "No" para todo e qualquer caso teria, portanto, uma exatidão próxima de 84% neste dataset.

Na presença de variáveis com distribuições altamente assimétricas, poderíamos, caso fosse conveniente, aplicar a transformação Box-Cox para corrigir tal assimetria. Deixaremos nossas variáveis como estão em relação à sua simetria.

Centralização e normalização

Por fim, vamos centralizar e normalizar o dataset para obter melhor comportamento em relação à certos algoritmos (por exemplo, algoritmos que envolvam otimização com método de gradiente ou similar).

```
transform <- preProcess(enc_HR, method=c("center", "scale"))
transformed_HR <- predict(transform, enc_HR)
```

Exportando

Podemos então exportar os dados para o formato csv, para continuar a modelagem em Python.

```
write_csv(transformed_HR, "transformed_HR.csv")
```