Risk Models Development Process

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1. 1. Data Preparation
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6. 6. Model selection
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1. Data Preparation

Data Preparation

- Model population
- Observation window
- Observation level
- Review of data systems
- Source data

Load data

```
Data <- read.csv('https://raw.githubusercontent.com/jakubszotek/Present
```

View data

```
print(head(Data,4), digits = 2, row.names = FALSE)
```

```
##  Customer_ID Date_of_data Default_date Country Industry
##            1   01/01/2014   24/11/2014      UK        A
##            2   01/01/2011                   UK        D
##            3   01/01/2018                   FR        A
##            4   01/01/2014   11/08/2014      FR        A
##  Length_of_business Total_assets Financial_leverage
##                 4.3          1.5                1.1
##                 8.7          9.8                1.2
##                 7.1          1.7                0.6
##                 5.6          6.2                1.2
##  Credit_limit   EDF GDP_growth Default
##          0.27 0.013       2.95       1
##          1.27 0.015       1.64       0
##          0.59 0.010       1.72       0
##          0.87 0.013       0.96       1
```

2. Analysis of risk parameters

All headers

```
sapply(Data, class)
```

```
##         Customer_ID        Date_of_data        Default_date
##           "integer"            "factor"            "factor"
##             Country            Industry Length_of_business
##            "factor"            "factor"           "numeric"
##        Total_assets Financial_leverage        Credit_limit
##           "numeric"           "numeric"           "numeric"
##                 EDF          GDP_growth             Default
##           "numeric"           "numeric"           "integer"
```

Default variable

```
head(Data,10) %>% select(Default_date, Default)
```

```
##    Default_date Default
## 1    24/11/2014       1
## 2                     0
## 3                     0
## 4    11/08/2014       1
## 5                     0
## 6    03/04/2012       1
## 7                     0
## 8                     0
## 9                     0
## 10                    0
```

Risk drivers

- Types of drivers:
  - Demographic
  - Financial
  - Behavioural
  - Macroeconomic
- Types of data:
  - Numerical
  - Boolean
  - Categorical

Risk drivers

```
Drivers <- Data %>% select(-Date_of_data,-Default_date)
print(head(Drivers,5), digits = 2, row.names = FALSE)
```

Risk drivers

```
##   Customer_ID Country Industry Length_of_business
## 1           1      UK        A                4.3
## 2           2      UK        D                8.7
## 3           3      FR        A                7.1
## 4           4      FR        A                5.6
## 5           5      UK        A                2.3
##   Total_assets Financial_leverage Credit_limit   EDF
## 1          1.5                1.1         0.27 0.013
## 2          9.8                1.2         1.27 0.015
## 3          1.7                0.6         0.59 0.010
## 4          6.2                1.2         0.87 0.013
## 5         15.9                1.3         1.87 0.018
##   GDP_growth Default
## 1       2.95       1
## 2       1.64       0
## 3       1.72       0
## 4       0.96       1
## 5       1.45       0
```

Single Factor Analysis - Univariate

- We exclude all variables having more than 10% of missing values
- Is there enough variance for each variable?

```
var_summary <- summary(Drivers %>% select(Country, Industry,
                                          Length_of_business,
                                          Total_assets,
                                          Financial_leverage,
                                          Credit_limit,
                                          EDF,
                                          GDP_growth))
```

Single Factor Analysis - Univariate

```
##  Country   Industry Length_of_business  Total_assets
##  DE:164    A:387    Min.    : 0.150     Min.    : 0.020
##  FR:302    B:106    1st Qu.: 2.670     1st Qu.: 1.278
##  PL:157    C:292    Median : 4.280     Median : 2.375
##  UK:377    D:215    Mean    : 4.915     Mean    : 3.088
##                     3rd Qu.: 6.372     3rd Qu.: 4.110
##                     Max.    :20.920     Max.    :15.940
##
##  Financial_leverage
##  Min.   :0.200
##  1st Qu.:0.680
##  Median :1.110
##  Mean   :1.121
##  3rd Qu.:1.587
##  Max.   :2.000
##  NA's   :158
```

Single Factor Analysis - Univariate

```
##   Credit_limit          EDF              GDP_growth
##  Min.   :0.0400   Min.   :0.00990   Min.   :0.310
##  1st Qu.:0.3500   1st Qu.:0.01020   1st Qu.:1.400
##  Median :0.5200   Median :0.01300   Median :1.790
##  Mean   :0.6001   Mean   :0.01405   Mean   :1.954
##  3rd Qu.:0.7800   3rd Qu.:0.01800   3rd Qu.:2.260
##  Max.   :2.2600   Max.   :0.02100   Max.   :5.150
##
```

Exclusions

- Financial_leverage has 158 N/A's out of 1000 observations (15.8%)

```
Drivers_1 = subset(Drivers, select=-c(Financial_leverage))
print(head(Drivers_1,5), digits = 2, row.names = FALSE)
```

```
##  Customer_ID Country Industry Length_of_business
##            1      UK        A                4.3
##            2      UK        D                8.7
##            3      FR        A                7.1
##            4      FR        A                5.6
##            5      UK        A                2.3
##  Total_assets Credit_limit   EDF GDP_growth Default
##           1.5         0.27 0.013       2.95       1
##           9.8         1.27 0.015       1.64       0
##           1.7         0.59 0.010       1.72       0
##           6.2         0.87 0.013       0.96       1
##          15.9         1.87 0.018       1.45       0
```

Further modifications

- Handling outliers
- Dealing with missing values if needed
- Transformations:
    - exponential
    - logarithmic
    - polynomial

Single Factor Analysis - Bivariate - Country

- We check the relationship between risk drivers and default

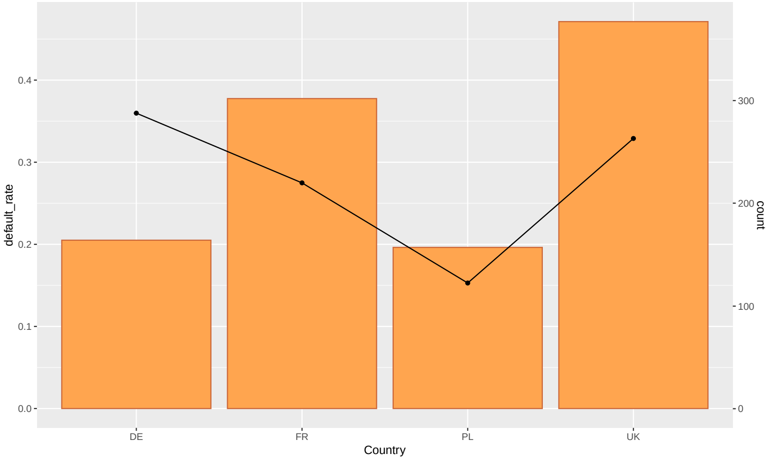
```
country_group <- Data %>% group_by(Country) %>%
  summarise(default_rate = mean(Default),count = n())
print(country_group, digits = 3, row.names = FALSE)
```

```
## # A tibble: 4 x 3
##   Country default_rate count
##   <fct>          <dbl> <int>
## 1 DE             0.360   164
## 2 FR             0.275   302
## 3 PL             0.153   157
## 4 UK             0.329   377
```

Single Factor Analysis - Bivariate - Country

```
ggplot(data=country_group, aes(x=Country, y=default_rate,
                               group=1)) +
    geom_bar(aes(x=Country, y=count/800),stat="identity",
         fill="tan1", colour="sienna3")+
    geom_line() +
    geom_point()+
    scale_y_continuous(name = waiver(),
                  sec.axis = sec_axis(~ . * 800,
                                      name = "count"))
```

Single Factor Analysis - Bivariate - Country



Single Factor Analysis - Bivariate - Country

- Switch from categorical variable Country to boolean Country_PL
- Is this in line with common sense and expectations?
- What is the expected impact of the variable on the final model?

Single Factor Analysis - Bivariate - Country

```
Drivers_2 <- Drivers_1
Drivers_2$Country_PL <- (Drivers_1$Country == "PL")*1
```

Single Factor Analysis - Bivariate - Country

```
##  Country Industry Length_of_business Total_assets
##       UK        A                4.3          1.5
##       UK        D                8.7          9.8
##       FR        A                7.1          1.7
##       FR        A                5.6          6.2
##       UK        A                2.3         15.9
##       UK        B                4.1          7.3
##       PL        A                3.2          4.2
##  Credit_limit   EDF GDP_growth Default Country_PL
##          0.27 0.013       2.95       1          0
##          1.27 0.015       1.64       0          0
##          0.59 0.010       1.72       0          0
##          0.87 0.013       0.96       1          0
##          1.87 0.018       1.45       0          0
##          0.73 0.018       1.45       1          0
##          0.66 0.013       3.32       0          1
```

Single Factor Analysis - Bivariate - Country

We remove the variable Country now

```
Drivers_2 <- subset(Drivers_2, select=-c(Country))
print(head(Drivers_2,7), digits = 2, row.names = FALSE)
```

Single Factor Analysis - Bivariate - Country

We remove the variable Country now

```
##   Industry Length_of_business Total_assets Credit_limit
## 1        A                4.3          1.5         0.27
## 2        D                8.7          9.8         1.27
## 3        A                7.1          1.7         0.59
## 4        A                5.6          6.2         0.87
## 5        A                2.3         15.9         1.87
## 6        B                4.1          7.3         0.73
## 7        A                3.2          4.2         0.66
##     EDF GDP_growth Default Country_PL
## 1 0.013       2.95       1          0
## 2 0.015       1.64       0          0
## 3 0.010       1.72       0          0
## 4 0.013       0.96       1          0
## 5 0.018       1.45       0          0
## 6 0.018       1.45       1          0
## 7 0.013       3.32       0          1
```

Single Factor Analysis - Bivariate - Industry

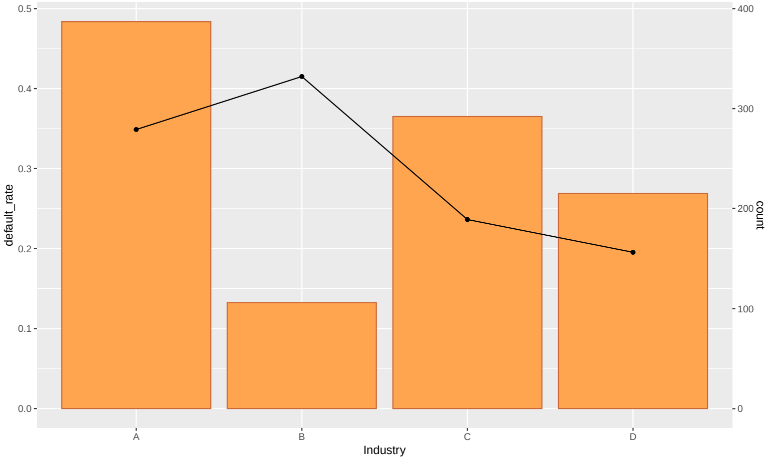
```
industry_group <- Data %>% group_by(Industry) %>%
  summarise(default_rate = mean(Default),count = n())
print(industry_group, digits = 3, row.names = FALSE)
```

```
## # A tibble: 4 x 3
##   Industry default_rate count
##   <fct>           <dbl> <int>
## 1 A               0.349   387
## 2 B               0.415   106
## 3 C               0.236   292
## 4 D               0.195   215
```

Single Factor Analysis - Bivariate - Industry

```r
ggplot(data=industry_group, aes(x=Industry, y=default_rate,
                                group=1)) +
    geom_bar(aes(x=Industry, y=count/800),stat="identity",
             fill="tan1", colour="sienna3")+
    geom_line() +
    geom_point()+
    scale_y_continuous(name = waiver(),
                       sec.axis = sec_axis(~ . * 800,
                                           name = "count"))
```

Single Factor Analysis - Bivariate - Industry



Single Factor Analysis - Bivariate - Industry

- Switch from categorical variables Industry $\in \{A, B\}$ to boolean Industry_AB
- Is this in line with common sense and expectations?
- What is the expected impact of the variable on the final model?

Single Factor Analysis - Bivariate - Industry

```
Drivers_3 <- Drivers_2
Drivers_3$Industry_AB <- (Drivers_2$Industry %in% c("A","B"))*1
print(head(subset(Drivers_3, select=-c(Customer_ID)),7),
      digits = 2, row.names = FALSE)
```

Single Factor Analysis - Bivariate - Industry

```
##   Industry Length_of_business Total_assets Credit_limit
##          A                4.3          1.5         0.27
##          D                8.7          9.8         1.27
##          A                7.1          1.7         0.59
##          A                5.6          6.2         0.87
##          A                2.3         15.9         1.87
##          B                4.1          7.3         0.73
##          A                3.2          4.2         0.66
##     EDF GDP_growth Default Country_PL Industry_AB
##   0.013       2.95       1          0           1
##   0.015       1.64       0          0           0
##   0.010       1.72       0          0           1
##   0.013       0.96       1          0           1
##   0.018       1.45       0          0           1
##   0.018       1.45       1          0           1
##   0.013       3.32       0          1           1
```

Single Factor Analysis - Bivariate - Industry

```
##  Length_of_business Total_assets Credit_limit   EDF
##                 4.3          1.5         0.27 0.013
##                 8.7          9.8         1.27 0.015
##                 7.1          1.7         0.59 0.010
##                 5.6          6.2         0.87 0.013
##                 2.3         15.9         1.87 0.018
##                 4.1          7.3         0.73 0.018
##                 3.2          4.2         0.66 0.013
##  GDP_growth Default Country_PL Industry_AB
##        2.95       1          0           1
##        1.64       0          0           0
##        1.72       0          0           1
##        0.96       1          0           1
##        1.45       0          0           1
##        1.45       1          0           1
##        3.32       0          1           1
```

Single Factor Analysis - Bivariate - Length_of_business

Let's bucket the data by year

```
## # A tibble: 19 x 3
##    Length_of_business_Floor default_rate count
##                       <dbl>        <dbl> <int>
##  1                        0       0.469     32
##  2                        1       0.459    111
##  3                        2       0.377    167
##  4                        3       0.384    151
##  5                        4       0.271    140
##  6                        5       0.266    109
##  7                        6       0.2       85
##  8                        7       0.138     58
##  9                        8       0.1       50
## 10                        9       0.121     33
## 11                       10       0.0714    14
## 12                       11       0         13
## 13                       12       0         12
## 14                       13       0.167      6
```

Single Factor Analysis - Bivariate - Length_of_business

Let's cut the dataset in 11 and put everything longer than that into one group

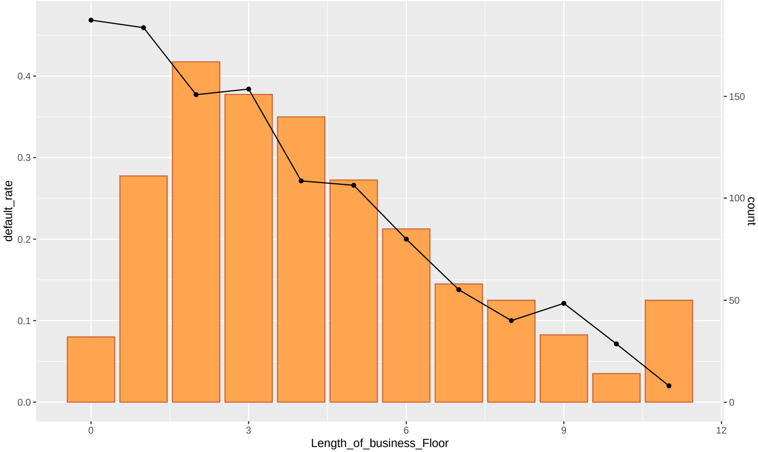
```
## # A tibble: 12 x 3
##    Length_of_business_Floor default_rate count
##                       <dbl>        <dbl> <int>
##  1                        0       0.469     32
##  2                        1       0.459    111
##  3                        2       0.377    167
##  4                        3       0.384    151
##  5                        4       0.271    140
##  6                        5       0.266    109
##  7                        6       0.2       85
##  8                        7       0.138     58
##  9                        8       0.1       50
## 10                        9       0.121     33
## 11                       10       0.0714    14
## 12                       11       0.02      50
```

Single Factor Analysis - Bivariate - Length_of_business

```
ggplot(data=length_group, aes(x=Length_of_business_Floor,
                              y=default_rate, group=1)) +
    geom_bar(aes(x=Length_of_business_Floor, y=count/400),
             stat="identity",
             fill="tan1", colour="sienna3")+
    geom_line() +
    geom_point()+
    scale_y_continuous(name = waiver(),
                       sec.axis = sec_axis(~ . * 400,
                                           name = "count"))
```

Single Factor Analysis - Bivariate - Length_of_business

- Is this relation in line with logic?



Single Factor Analysis - Bivariate - Total_assets

```
Data$Total_assets_Floor <- floor(Data$Total_assets)
assets_group <- Data %>% group_by(
  Total_assets_Floor) %>% summarise(
    default_rate = mean(Default),count = n())
print(assets_group, digits = 3, row.names = FALSE)
```

Single Factor Analysis - Bivariate - Total_assets

```
## # A tibble: 16 x 3
##    Total_assets_Floor default_rate count
##                 <dbl>        <dbl> <int>
##  1                  0        0.320   181
##  2                  1        0.322   236
##  3                  2        0.304   184
##  4                  3        0.321   134
##  5                  4        0.207    87
##  6                  5        0.255    55
##  7                  6        0.268    41
##  8                  7        0.167    30
##  9                  8        0.15     20
## 10                  9        0.167     6
## 11                 10        0.167     6
## 12                 11        0.222     9
## 13                 12        0         4
## 14                 13        0.5       4
## 15                 14        0         1
```

Single Factor Analysis - Bivariate - Total_assets

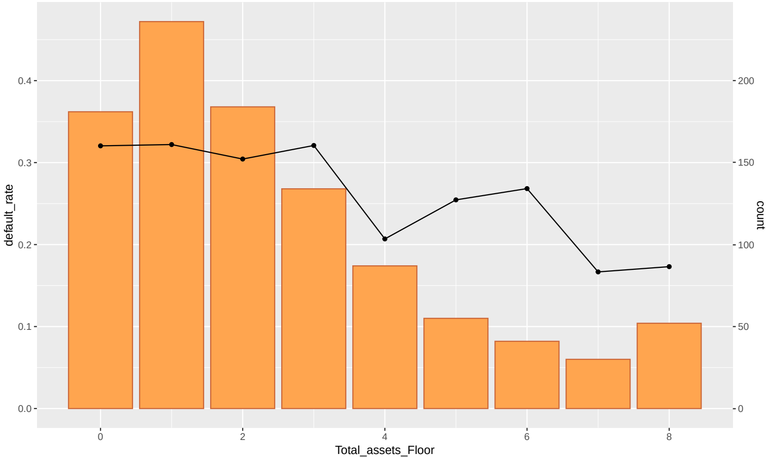
Let's cut the dataset in 8 and put everything longer than that into one group

```
## # A tibble: 9 x 3
##   Total_assets_Floor default_rate count
##                <dbl>        <dbl> <int>
## 1                  0        0.320   181
## 2                  1        0.322   236
## 3                  2        0.304   184
## 4                  3        0.321   134
## 5                  4        0.207    87
## 6                  5        0.255    55
## 7                  6        0.268    41
## 8                  7        0.167    30
## 9                  8        0.173    52
```

Single Factor Analysis - Bivariate - Total_assets

```
ggplot(data=assets_group, aes(x=Total_assets_Floor, y=default_rate,
                              group=1)) +
    geom_bar(aes(x=Total_assets_Floor, y=count/500),
             stat="identity",
             fill="tan1", colour="sienna3")+
    geom_line() +
    geom_point()+
    scale_y_continuous(name = waiver(),
                       sec.axis = sec_axis(~ . * 500,
                                           name = "count"))
```

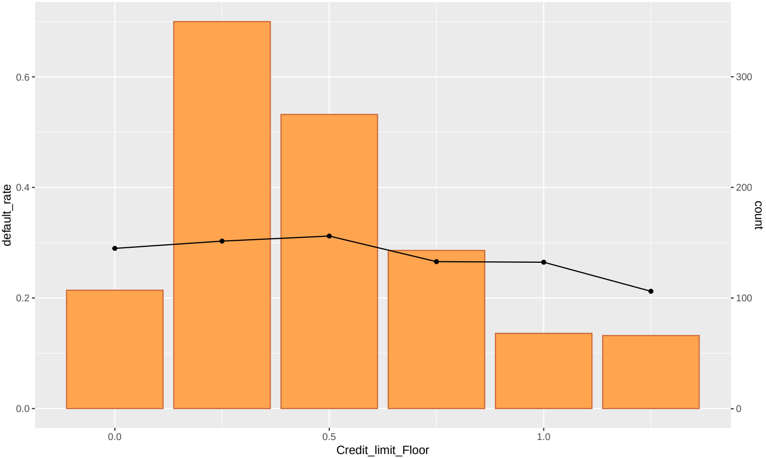
Single Factor Analysis - Bivariate - Total_assets



Single Factor Analysis - Bivariate - Credit_limit

```
## # A tibble: 6 x 3
##   Credit_limit_Floor default_rate count
##                <dbl>        <dbl> <int>
## 1               0           0.290   107
## 2               0.25        0.303   350
## 3               0.5         0.312   266
## 4               0.75        0.266   143
## 5               1           0.265    68
## 6               1.25        0.212    66
```

Single Factor Analysis - Bivariate - Credit_limit



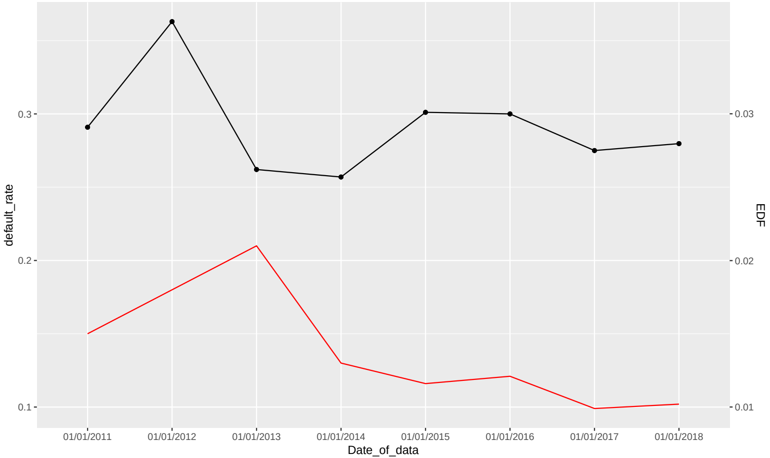
Single Factor Analysis - Bivariate - Expected Default Frequency

EDF is a variable common to all debtors dependent on year

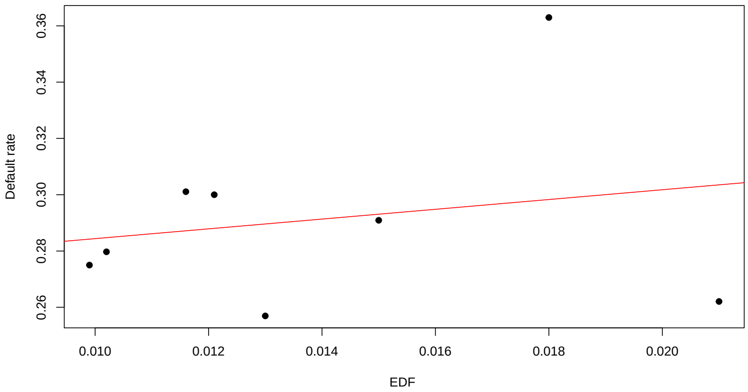
```
EDF_group <- Data %>% group_by(Date_of_data) %>%
  summarise(default_rate = mean(Default), EDF = mean(EDF),
            count = n())
print(EDF_group, digits = 3, row.names = FALSE)
```

```
## # A tibble: 8 x 4
##   Date_of_data default_rate    EDF count
##   <fct>               <dbl>  <dbl> <int>
## 1 01/01/2011          0.291 0.015    110
## 2 01/01/2012          0.363 0.018    135
## 3 01/01/2013          0.262 0.021    145
## 4 01/01/2014          0.257 0.013    144
## 5 01/01/2015          0.301 0.0116    93
## 6 01/01/2016          0.3   0.0121   110
## 7 01/01/2017          0.275 0.0099   120
## 8 01/01/2018          0.280 0.0102   143
```

Single Factor Analysis - Bivariate - Expected Default Frequency



Single Factor Analysis - Bivariate - Expected Default Frequency




```
## integer(0)
```

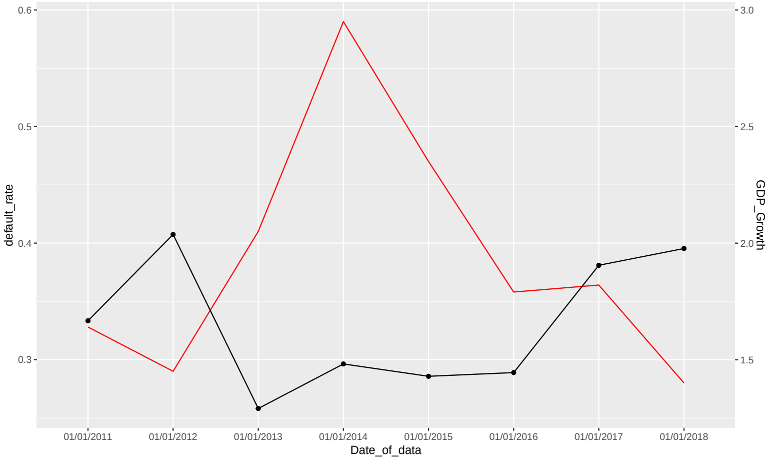
Single Factor Analysis - Bivariate - GDP_growth

GDP_growth is a variable common to all debtors dependent on year and country

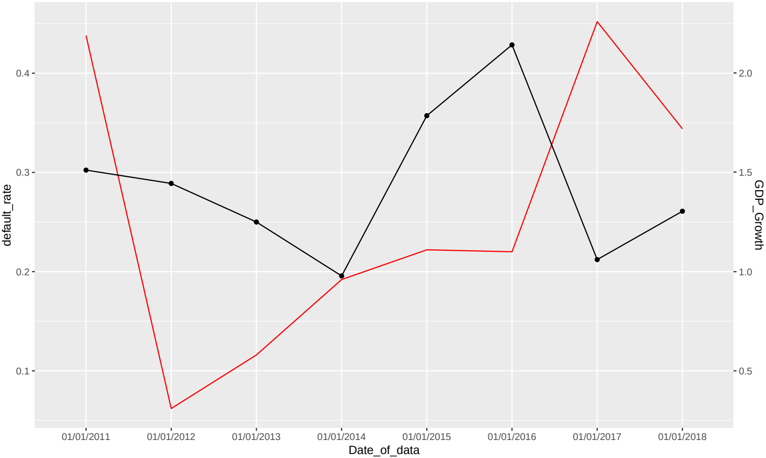
```
GDP_group <- Data %>% group_by(Date_of_data,Country) %>%
  summarise(default_rate = mean(Default),GDP_growth = mean(GDP_growth))
print(GDP_group, digits = 3, row.names = FALSE)
```

```
## # A tibble: 32 x 4
## # Groups:   Date_of_data [8]
##    Date_of_data Country default_rate GDP_growth
##    <fct>        <fct>          <dbl>      <dbl>
##  1 01/01/2011   DE            0.286        3.66
##  2 01/01/2011   FR            0.302        2.19
##  3 01/01/2011   PL            0.0909       5.02
##  4 01/01/2011   UK            0.333        1.64
##  5 01/01/2012   DE            0.474        0.49
##  6 01/01/2012   FR            0.289        0.31
##  7 01/01/2012   PL            0.294        1.61
##  8 01/01/2012   UK            0.407        1.45
```

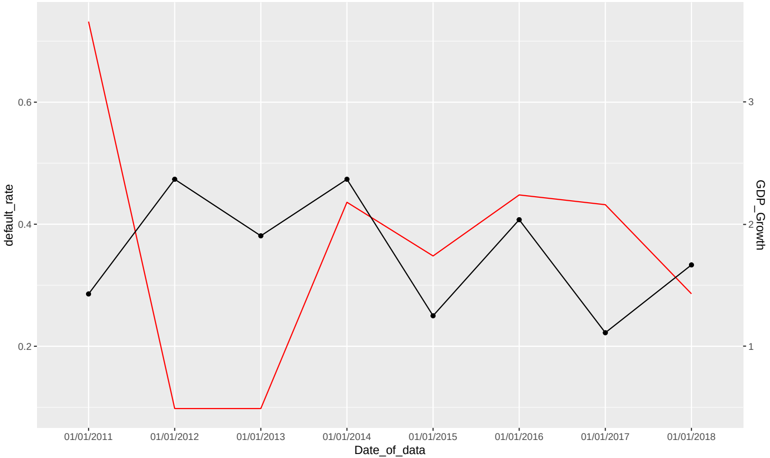
Single Factor Analysis - Bivariate - GDP_growth - UK



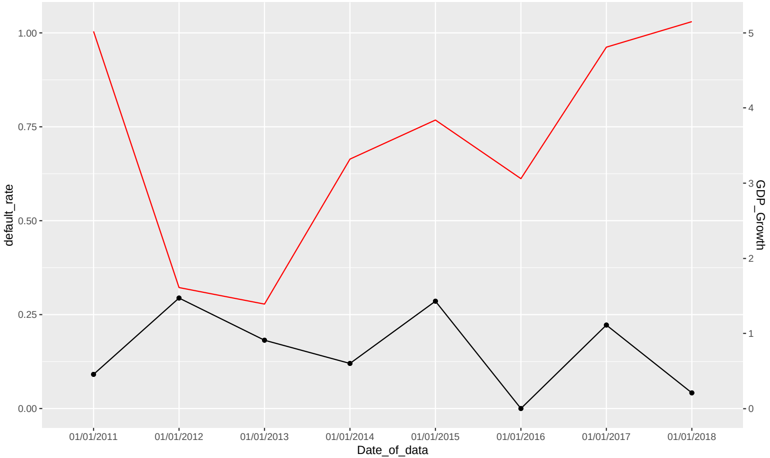
Single Factor Analysis - Bivariate - GDP_growth - FR



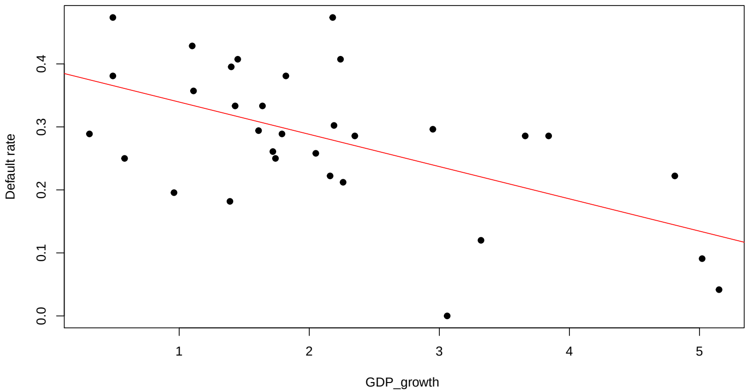
Single Factor Analysis - Bivariate - GDP_growth - DE



Single Factor Analysis - Bivariate - GDP_growth - PL



Single Factor Analysis - Bivariate - GDP_growth - All countries




```
## integer(0)
```

Final dataset

```r
Drivers_final <- Drivers_3[, c("Country_PL","Industry_AB",
                  "Length_of_business","Total_assets","Credit_limit",
                  "EDF","GDP_growth","Default")]
print(head(Drivers_final,5), digits = 2, row.names = FALSE)
```

```
##  Country_PL Industry_AB Length_of_business Total_assets
##           0           1                4.3          1.5
##           0           0                8.7          9.8
##           0           1                7.1          1.7
##           0           1                5.6          6.2
##           0           1                2.3         15.9
##  Credit_limit   EDF GDP_growth Default
##          0.27 0.013       2.95       1
##          1.27 0.015       1.64       0
##          0.59 0.010       1.72       0
##          0.87 0.013       0.96       1
##          1.87 0.018       1.45       0
```

3. Data split

Development sample

- Data that we use to estimate model parameters
- Usually between 75% and 90% of the whole sample

```
set.seed(101)
sample = sample.split(Drivers_final$Default, SplitRatio = .80)
development_sample = subset(Drivers_final, sample == TRUE)
```

Hold-out sample

- Data that we use to evaluate the performance of the model
- Usually between 10% and 25% of the whole sample

```
hold_out_sample  = subset(Drivers_final, sample == FALSE)
```

4. Model functional form

Model functional form

Possible methods for PD modelling:

- Probit model
- Logistic regression
- Scoring models
- Machine learning
- Neural networks

Logistic Regression

$$\ln\left\{\frac{P[Y=1|X]}{P[Y=0|X]}\right\} = \beta_0 + X\beta$$

with $X = (X_1, X_2, \ldots, X_N)$ the set of prognostic factors. Assuming a linear model for f_n, the probability that $Y = 1$ is modelled as:

$$y = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots)}}$$

In R, this regression can be fitted with the function `glm()`.

5. Multiple Factor Analysis

Number of possible models

- We have 7 input variables (risk drivers) and 1 modelled variable
- The number of possible models: $2^7 - 1 = 127$.

```
variables = colnames(Drivers_final)
variables
```

```
## [1] "Country_PL"         "Industry_AB"
## [3] "Length_of_business" "Total_assets"
## [5] "Credit_limit"       "EDF"
## [7] "GDP_growth"         "Default"
```

Exemplary model

```
m0 <- glm(data = development_sample,
          formula = Default ~ Country_PL + Industry_AB +
                                        Total_assets + Credit_limit + EDF,
         family = binomial)
summary(m0)[12]
```

Exemplary model

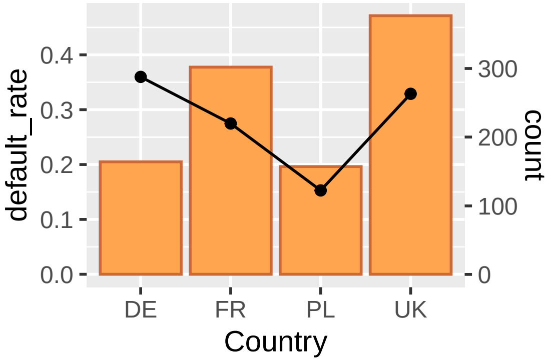
```
## $coefficients
##                  Estimate  Std. Error    z value
## (Intercept)    -0.6016979  0.35144990 -1.7120445
## Country_PL     -0.9552921  0.26030418 -3.6699068
## Industry_AB     0.7913721  0.16323447  4.8480697
## Total_assets   -0.1156390  0.04670397 -2.4759986
## Credit_limit    0.2254393  0.33022570  0.6826825
## EDF           -26.7674014 21.20266772 -1.2624544
##                  Pr(>|z|)
## (Intercept)  8.688847e-02
## Country_PL   2.426389e-04
## Industry_AB  1.246686e-06
## Total_assets 1.328641e-02
## Credit_limit 4.948075e-01
## EDF          2.067853e-01
```

Exemplary model

```
##          Driver Sign Estimate
## 1    Country_PL    -    -0.96
## 2   Industry_AB    +     0.79
## 3  Total_assets    -    -0.12
## 4  Credit_limit   -?     0.23
## 5           EDF   +?   -26.77
```

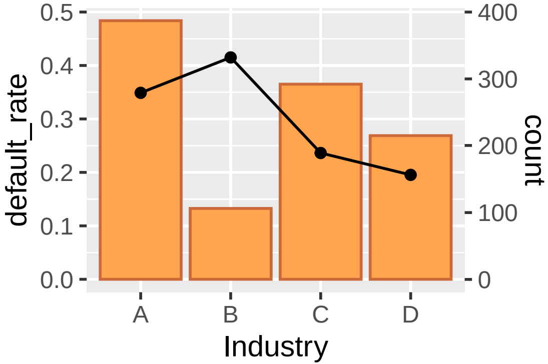
Acceptance criteria - No counterintuitive signs

```
##        Driver Sign Estimate
## 1 Country_PL    -    -0.96
```



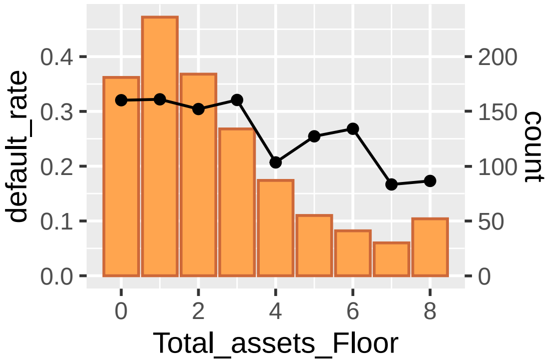
Acceptance criteria - No counterintuitive signs

```
##         Driver Sign Estimate
## 2 Industry_AB    +     0.79
```



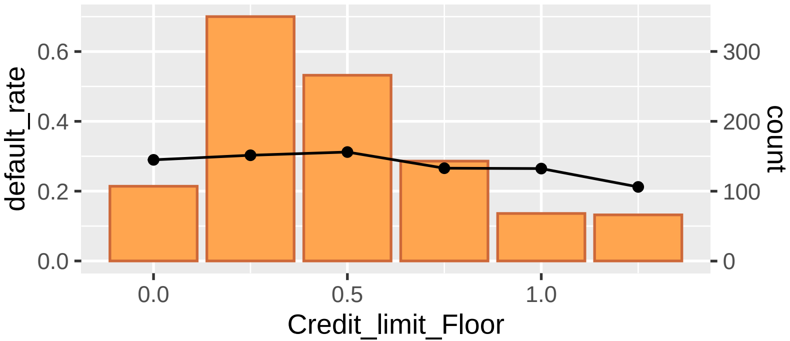
Acceptance criteria - No counterintuitive signs

```
##          Driver Sign Estimate
## 3 Total_assets    -    -0.12
```



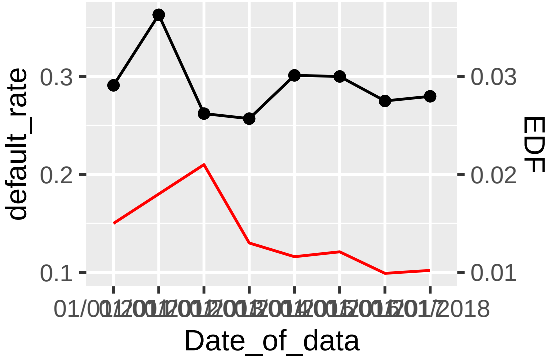
Acceptance criteria - No counterintuitive signs

```
##          Driver Sign Estimate
## 4 Credit_limit   -?     0.23
```



Acceptance criteria - No counterintuitive signs

```
##   Driver Sign Estimate
## 5    EDF   +?      -27
```



Acceptance criteria - p-value

```
summary <- data.frame(coef(summary(m0))[,c(1,4)])
summary$p_val_less_5PRC <- summary[,2] <= 0.05
summary
```

```
##                  Estimate     Pr...z.. p_val_less_5PRC
## (Intercept)    -0.6016979 8.688847e-02           FALSE
## Country_PL     -0.9552921 2.426389e-04            TRUE
## Industry_AB     0.7913721 1.246686e-06            TRUE
## Total_assets   -0.1156390 1.328641e-02            TRUE
## Credit_limit    0.2254393 4.948075e-01           FALSE
## EDF           -26.7674014 2.067853e-01           FALSE
```

Acceptance criteria - correlation

No two variables can be correlated more than 0.50 in absolute terms.

```
corr_data <- subset(development_sample,
                    select = c("Country_PL",
                               "Industry_AB",
                               "Total_assets",
                               "Credit_limit",
                               "EDF"))
correlation_results <- cor(corr_data)
```

Acceptance criteria - correlation

```
##              Country_PL Industry_AB Total_assets
## Country_PL       1.0000      -0.027       0.0053
## Industry_AB     -0.0271       1.000       0.0123
## Total_assets     0.0053       0.012       1.0000
## Credit_limit     0.0193      -0.025       0.7145
## EDF             -0.0395       0.068      -0.0405
##              Credit_limit    EDF
## Country_PL          0.019 -0.040
## Industry_AB        -0.025  0.068
## Total_assets        0.715 -0.040
## Credit_limit        1.000 -0.028
## EDF                -0.028  1.000
```

Acceptance criteria - Summary

- Expected sign
  - Credit_limit and EDF do not meet the criteria
- Significance (p-value)
  - Credit_limit and EDF do not meet the criteria
- Correlation
  - Total_assets and Credit_limit cannot appear in the same model

Result -> model rejected

Model search

An estimation is done for each possible model and only the models that fulfil all the criteria are considered further. In practice:

- models including correlated pairs of variables are not estimated
- regulatory requirements state that some kinds of variables need to be included, eg:
  - customer size or proxy
  - macroeconomic

6. Model selection

Model selection - performance criteria

For all the models that passed the acceptance criteria we calculate some performance metrics eg.:

- Gini coefficient - the higher the better
- Akaike information criterion (AIC) - the lower the better

AIC - Akaike Information Criteria

$$AIC = 2k - 2ln(\hat{L}),$$

where:

k - number of parameters (penalize more parameters)

$\hat{L}$ - likelihood function (promote higher likelihood)

Model selection - performance criteria

Let's compare three models:

- m1: Default ~ Industry_AB + Length_of_business + Total_assets
- m2: Default ~ Country_PL + Length_of_business + Total_assets
- m3: Default ~ Country_PL + Industry_AB + Length_of_business + Total_assets

Model selection - estimation of parameters

```
m1 <- glm(data = development_sample,
          formula = Default ~ Industry_AB + Length_of_business +
                              Total_assets,
          family = binomial)
m2 <- glm(data = development_sample,
          formula = Default ~ Country_PL + Length_of_business +
                              Total_assets,
          family = binomial)
m3 <- glm(data = development_sample,
          formula = Default ~ Country_PL + Industry_AB +
                              Length_of_business + Total_assets,
          family = binomial)
```

Model selection - Gini

We predict the probabilities for each model

```
development_sample$prediction_m1 =
              fitted.values(m1)
development_sample$prediction_m2 =
              fitted.values(m2)
development_sample$prediction_m3 =
              fitted.values(m3)
```

Model selection - Gini

```
print(head(subset(development_sample, select =
                    c(Default,prediction_m1,
                      prediction_m2,prediction_m3)),
           10),digits = 2)
```

```
##    Default prediction_m1 prediction_m2 prediction_m3
## 1        1         0.406         0.357         0.440
## 2        0         0.043         0.071         0.048
## 4        1         0.237         0.202         0.259
## 5        0         0.235         0.207         0.255
## 6        1         0.297         0.259         0.324
## 8        0         0.390         0.343         0.423
## 9        0         0.311         0.269         0.339
## 10       0         0.331         0.463         0.365
## 12       0         0.195         0.293         0.218
## 13       0         0.568         0.283         0.357
```

Model selection - Gini

```
model_summary <- data.frame(
              "Model"= c("m1","m2","m3"),
              "Gini_development" =
                c(Gini(development_sample$prediction_m1,
                        development_sample$Default),
                  Gini(development_sample$prediction_m2,
                        development_sample$Default),
                  Gini(development_sample$prediction_m3,
                        development_sample$Default)))
```

Model selection - Gini

```r
print(model_summary, digits = 3)
```

```
##   Model Gini_development
## 1    m1            0.215
## 2    m2            0.195
## 3    m3            0.228
```

Model selection - AIC

```
model_summary$AIC <- c(AIC(m1),AIC(m2),AIC(m3))
print(model_summary, digits = 3)
```

```
##   Model Gini_development AIC
## 1    m1            0.215 869
## 2    m2            0.195 872
## 3    m3            0.228 854
```

Model selection - Champion and Challenger

After the analysis of all possible models for all functional forms considered we choose:

- Champion model - best model (our m3)
- Challenger model - second best (our m1)

7. Model validation

Model validation

We need to check how our champion and challanger models perform on the hold-out sample

```
hold_out_sample$prediction_m3 <-predict(m3,
                      newdata = hold_out_sample, type = 'response')
hold_out_sample$prediction_m1 <-predict(m1,
                      newdata = hold_out_sample, type = 'response')
```

Validation - Gini

```
validation_summary <- data.frame(
              "Model"= c("m3","m1"),
              "Gini_hold_out" =
                c(Gini(hold_out_sample$prediction_m3,
                      hold_out_sample$Default),
                  Gini(hold_out_sample$prediction_m1,
                      hold_out_sample$Default)))
```

Validation - Gini

```r
print(validation_summary, digits = 3)
```

```
##   Model Gini_hold_out
## 1    m3         0.235
## 2    m1         0.232
```

Summarize

```
summary_final <- merge(x = model_summary,
                       y = validation_summary,
                       by = "Model",
                       all.y = TRUE) %>% subset(select=-c(AIC))
summary_final$Dev_minus_hold_out <-
  summary_final$Gini_development - summary_final$Gini_hold_out
```

Summarize

```
print(summary_final, digits = 3)
```

```
##   Model Gini_development Gini_hold_out Dev_minus_hold_out
## 1    m1            0.215         0.232            -0.0173
## 2    m3            0.228         0.235            -0.0063
```

Conclusions

- Both models seem to perform better on the hold-out sample than on the development sample
- The classification remains the same:
  - Champion: m3 - Default ~ Country_PL + Industry_AB + Length_of_business + Total_assets

```
print(coefficients(m3), digits = 3)
```

```
##         (Intercept)          Country_PL         Industry_AB
##              0.3462             -1.0112              0.7339
## Length_of_business        Total_assets
##             -0.2759             -0.0955
```

Conclusions

- Challenger: m1 - Default ~ Industry_AB + Length_of_business + Total_assets

```r
print(coefficients(m1), digits = 3)
```

```
##         (Intercept)         Industry_AB Length_of_business
##              0.1781              0.7392            -0.2712
##        Total_assets
##             -0.0927
```

End

THANK YOU!!!