Exploration of company information

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Contents

1 Scope and objectives

This notebook explores the datasets that will presumably underpin future research work for the PhD in Applied Data Science and Artificial Intelligence.

1.1 Background information:

Research, innovation and highly skilled people are considered to be important factors in economic and social development. Economic support policies often include funds to support research (for example with the creation of public research infrastructures), companies (for example with tenders to co-finance innovative projects) and the training of people with the necessary skills.

Area Science Park is a national research institution that manages a science and technology park located in Trieste (Italy). Its activities can be considered a public investment in support of research and innovation, for a value of approximately 20 million euros per year.

Currently Area is hosting 70 tenants (60 companies and 10 research centers) engaged in research activities in the fields of ICT, lifesceinces and materials. Their success (or lack of it) depends on a key - and often overlooked - asset: the community of over 1600 employees, researchers and entrepreneurs.

Area is interested in measuring the effectiveness and efficiency of its activities, focusing in particular on

- monitoring the economic performance of tenants,
- monitoring the community of skilled workers,
- comparing with similar groups, mainly at a regional or national scale, but also with respect to the science and technology parks in Austria and Slovenia.

To support research work, Area Science Park can provide some relevant datasets, cureated as a part of the project *innovation intelligence*. Innovation Intelligence aims to analyze information on companies in the Friuli Venezia Giulia region, using several data sources such as the chamber of commerce, the Regional Labor Market Observatory, a rating agency, as well as surveys on samples of companies.

1.2 Objectives of future research work - reserch questions

Research questions are currently defined on a general level:

- are tenant companies performing better than similar companies?
- how to measure similarity between two companies?
- how to exthed such measure to groups of companies?
- how to identify clusters or communities of companies?

The research questions above and the methodology outlined in this notebook are relevant also in other contexts, such ad sectoral cluster, public agencies supporting innovation and any kind of industrial area. The data set supports analysis focused on Friuli Venezia Giulia region, but can be extended to other regions (gathering relevant data from the Chamber of Commerce or from commercial data providers).

1.3 About this notebook

The notebook is divided in 6 sections: an introduction, a section for each dataset and a final section on potential future development.

1. Imprese_FVG
2. Bilanci_FVG
3. Rating_FVG
4. CO_FVG
5. Features: A basic example of sample feature selection, on a small subset, where each company is represented by 5 features
6. Further development: calculating the age of companies based on several dates, handling non metric features: defining a custimized similarity function to identify *similar* companies and estimate distances in a multi-dimensional space.

The notebook has been written using *R-Studio* and rendered with *boowdown* (https://bookdown.org/) package. Data data manipulation is based on *tidyverse* [https://www.tidyverse.org/], a data science library that includes *magrittr* (pipe operator %>%), *dplyr* (select, summarize...), *tibble* (a tidier version of the data.frame) and *ggplot2* (visualizations). A useful guide to tidverse is available online at the following address: [https://r4ds.had.co.nz/]

> TODO Some parts of the notebook are higlighted as “To Do”, to highlight potential improvements in analysis, code efficiency or need for further clarifications.

1.4 Data management plan

Raw data: The original data has been pre-pocessed by Area Science Park to fulfill the folloqing rquirements:

- encoded in UTF-8 cleaned from non-printable characters
- table columns are attributes (features, independent variables), renamed to be human- and machine-readable
- table rows are observations If you have multiple tables, they should include a column in the table that allows them to be linked
- splitted into several tables, created unique identifiers to connect the tables
- saved each table to separate .csv file with a hunam-readable name At this stage no attributes were removed or summarized. Raw data is available in local folder *data/raw*

Tidy data: This notebook explores all the attributes available in the raw data, and by merging, subsetting and transforming, produces a smaller, cleaner data set ready for further analysis. Tidy data is saved in local folder *data/tidy*

This notebook describes the process to create tidy data, and the meaning of each variable: - meaning, summary and visualizations ofeach attribute in tidy data - information about attributes that are not contained in the tidy data (basic meaning and reason why thy have not been included)

Updates: raw and tidy data may be updated periodically, since Area Science Park updates the raw data set twice a year; anyway the current version in based on June 2021 version and does not provide automatic updating scripts.

2 Exploring dataset “companiesFVG”

The dataset is organizes in a number of files; each file will be loaded in a different *data.frame*.

```
data.files <- list.files(pathRawData, pattern = ".csv$", recursive = TRUE)
print(paste("dataset contains",length(data.files), "files:"))
```

```
## [1] "dataset contains 10 files:"
```

```
print(data.files)
```

```
##  [1] "bilanci-fvg.csv"          "d_ateco.csv"
##  [3] "d_ng.csv"                 "id_imp_loc.csv"
##  [5] "pseudo_cf_id_impresa.csv" "t_attivita.csv"
##  [7] "t_codici.csv"             "t_imprese.csv"
##  [9] "t_imprese_dp.csv"         "t_localizz.csv"
```

2.1 companies

The core data identifying companies can be found in *t_imprese.csv* .

```
companies <- read_delim( paste0(pathRawData,"/t_imprese.csv"))
```

```
## Rows: 108379 Columns: 34
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: "|"
## chr  (19): fonte, mm_aaaa, denominazione, cf, piva, prov, reg_imp_n, sede_ul...
## dbl   (5): id_impresa, addetti_aaaa, addetti_indip, addetti_dip, capitale
## lgl   (2): data_canc, imp_sedi_ee
## date  (8): data_cost, data_isc_ri, data_isc_rd, data_isc_aa, data_ini_at, da...
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message
```

```
spec(companies) # tydiverse for str(companies)
```

```
## cols(
##   fonte = col_character(),
##   mm_aaaa = col_character(),
##   id_impresa = col_double(),
##   denominazione = col_character(),
##   cf = col_character(),
##   piva = col_character(),
##   prov = col_character(),
##   reg_imp_n = col_character(),
##   sede_ul = col_character(),
##   `n-albo_art` = col_character(),
##   reg_imp_sez = col_character(),
##   ng2 = col_character(),
##   stato_impresa = col_character(),
##   data_cost = col_date(format = ""),
##   data_isc_ri = col_date(format = ""),
##   data_isc_rd = col_date(format = ""),
##   data_isc_aa = col_date(format = ""),
##   data_canc = col_logical(),
##   data_ini_at = col_date(format = ""),
##   data_cess_att = col_date(format = ""),
##   data_fall = col_date(format = ""),
##   data_liquid = col_date(format = ""),
##   addetti_aaaa = col_double(),
##   addetti_indip = col_double(),
##   addetti_dip = col_double(),
##   capitale = col_double(),
##   capitale_valuta = col_character(),
##   imp_sedi_ee = col_logical(),
##   imp_eefvg = col_character(),
##   imp_pmi = col_character(),
##   imp_startup = col_character(),
##   imp_femminile = col_character(),
##   imp_giovanile = col_character(),
##   imp_straniera = col_character()
## )
```

The attributes belong to different groups:

- *metadata*:ï..fonte, mm_aaaa:
- *identifier*: id_impresa,reg_imp_n, cf, piva, denominazione
- *address*:prov,sede_ul,n.albo_art,reg_imp_sez

- *type of company*: ng2
- *active status*: stato_impresa

- *dates*:data_ini_at, data_cess_att, data_fall, data_liquid, data_cost, data_isc_ri, data_isc_rd,data_isc_aa,data_canc
- *employees*: addetti_aaaa, addetti_indip, addetti_dip

- *share capital*: capitale, capitale_valuta
- *other attributes*: imp_startup, imp_femminile, imp_giovanile, imp_straniera, imp_pmi, imp_sedi_ee, imp_eefvg

2.1.1 Metadata

Metadata are generated by the pre-rpcessing algorithm and provide information about source and last update. The two attributes (ï..fonte, mm_aaaa) are not relevant at this stage.

```
companies <- companies %>% select( !c(fonte, mm_aaaa))
#same as subset(companies, select = -c(ï..fonte, mm_aaaa))
```

2.1.2 Identifiers

The following attributes are relevant: - denominazione: company name - cf ("codice fiscale"): unique identifier, as factor (11 numbers or a string of 16 lettersa nd numbers) - id_impresa: unique identifier, numeric. Id and cf are unique, while company names are not and there are no missing values. Other attributes (reg_imp_n,piva, n.albo_art,reg_imp_sez) are not relevant at this stage, and can be dropped.

TOTO the name of attribute `n-albo_art`should not contain "-"

```
companies <- companies %>%
             select( !c(reg_imp_n, piva, `n-albo_art`,reg_imp_sez)) %>%
             rename(name = denominazione) %>%
             rename(idCompany = id_impresa) %>%
             mutate_if(is.character, as.factor)
```

Now we can ckeck if there are any missing values or duplicates

```
# check missing calues
sum(is.na(companies$name)) + sum(is.na(companies$cf)) == 0
```

```
## [1] TRUE
```

```
# check duplicates in cf
length(unique(companies$cf)) == length(companies$cf)
```

```
## [1] TRUE
```

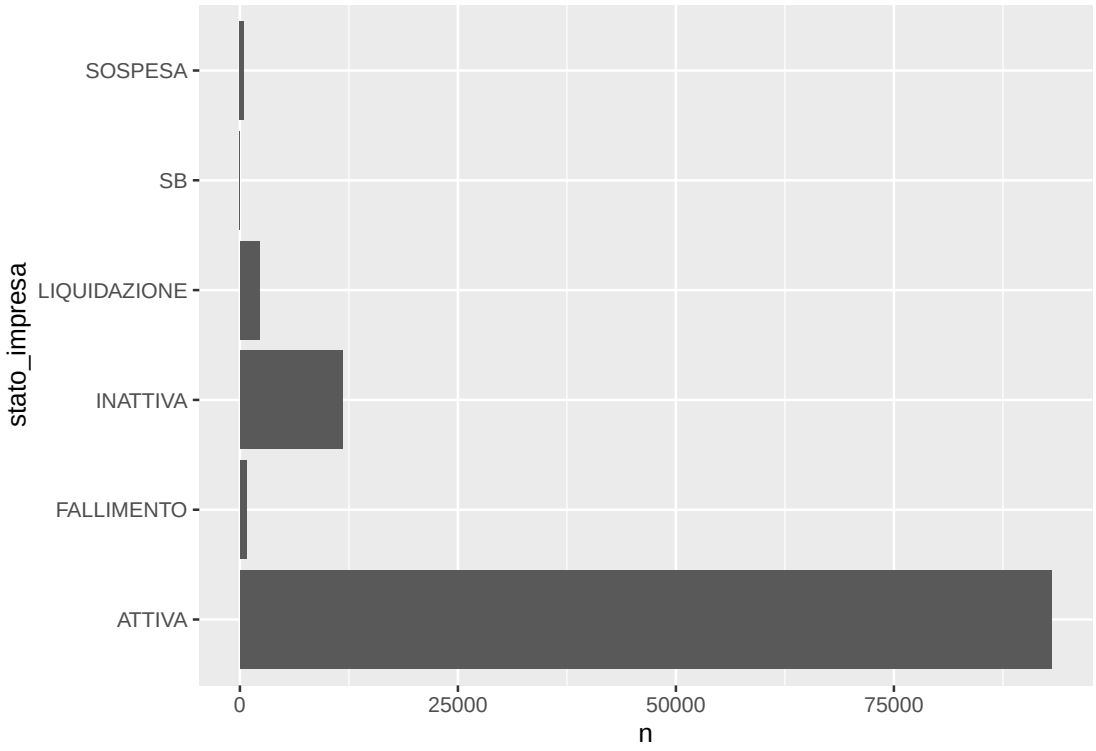
```
# check duplicates in name
uniqueNames <-length(unique(companies$name))
allNames<-length(companies$name)
print(paste("Company names are not a valid identifier for further analysis: the dat
```

```
## [1] Company names are not a valid identifier for further analysis: the dataset c
```

2.1.3 active status

Companies that are not active (e.g. due to bankruptcy, liquidation or suspended) are not relevant for the research objectives and can be removed from the dataset.

```
df<-companies %>% count(stato_impresa)
ggplot(data=df, aes(x=stato_impresa, y=n)) +   geom_bar(stat="identity") + coord_fl
```




```
companies <- subset(companies, stato_impresa =='ATTIVA')
print(paste("Number of active companies: ", nrow(companies)), quote=FALSE)
```

```
## [1] Number of active companies:  93106
```

2.1.4 location

Each company has a "registered office" (sede legale) and may have several local units (unità locale). Relevant data is stored in file "t_localizz.csv". > TODO: add description of variables. Select only companies that are located in Friuli Venezia Giulia, according to prov: province (GO, TS, UD, PN). Select companies that have head office abroad. sede_ul: "SEDE" or "UL-n" » factor SEDE = HeadOffice / UL = LocalUnit Extract the number of local units from attribute "sede_ul" Create new variable "head-office" true/false use "data apertura ul" to improve the estimate of company age (or remove the attribute) remove unnecessary variables

```
locs <- read_delim( paste0(pathRawData,"/t_localizz.csv")) %>%
             select( c(id_localiz, id_impresa, denominazione,tipo_localizzazione)) %>%
             rename(name = denominazione) %>%
```

```
            rename(idCompany = id_impresa) %>%
            mutate_if(is.character, as.factor)
```

```
## Rows: 205385 Columns: 10
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: "|"
## chr  (7): fonte, denominazione, tipo_localizzazione, prov_localiz, comune, i...
## dbl  (2): id_localiz, id_impresa
## dttm (1): data_apert_ul
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message
```

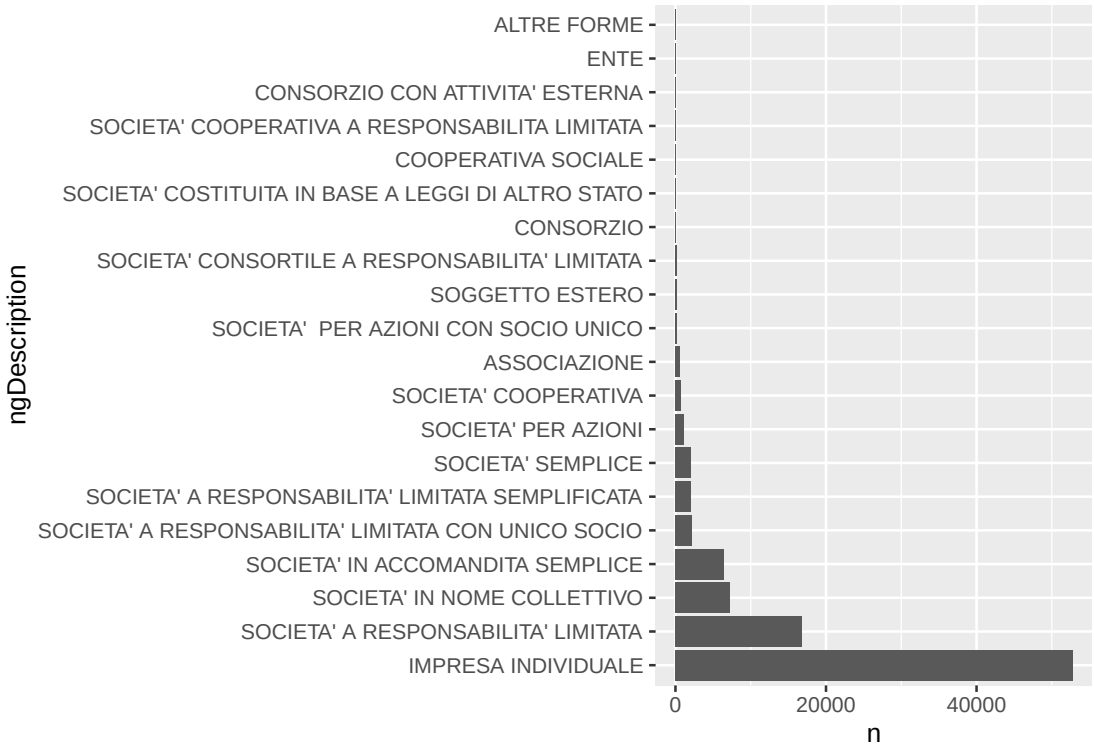
2.1.5 type of company

TODO: add text. improve code with tidyverse

```
# company type: keep only the relevan ones for the scope of our research.
types <- read.csv( paste0(pathRawData,"/d_ng.csv"), sep = "|")
companies$ng2           <- as.factor(companies$ng2)
names(types)<-c("ngGroup", "ng2", "ngDescription")

df <- companies  %>% count(ng2)
df <- df %>% inner_join(types)
```

```
## Joining, by = "ng2"
```

```
df <- df  %>% arrange(-n) %>% head(20)
df$ngDescription <- factor(df$ngDescription, levels = df$ngDescription) #lock facto
ggplot(data=df, aes(x=ngDescription, y=n)) +   geom_bar(stat="identity") + coord_fl
```



Some company types are not relevant for our research, for example individual companies (DI) and other specified below. Dropping the corresponding dataframe rows drastically reduces the size of the data set

```
notRelevant = c("DI", "AZ", "IR", "ER", "EP", "EN", "EM", "EL", "EE", "SM", "MA", "SZ", "LL",
toBeRemoved<-which(companies$ng2 %in% notRelevant)
companies2<-companies[-toBeRemoved,]
print(nrow(companies2))
```

```
## [1] 40211
```

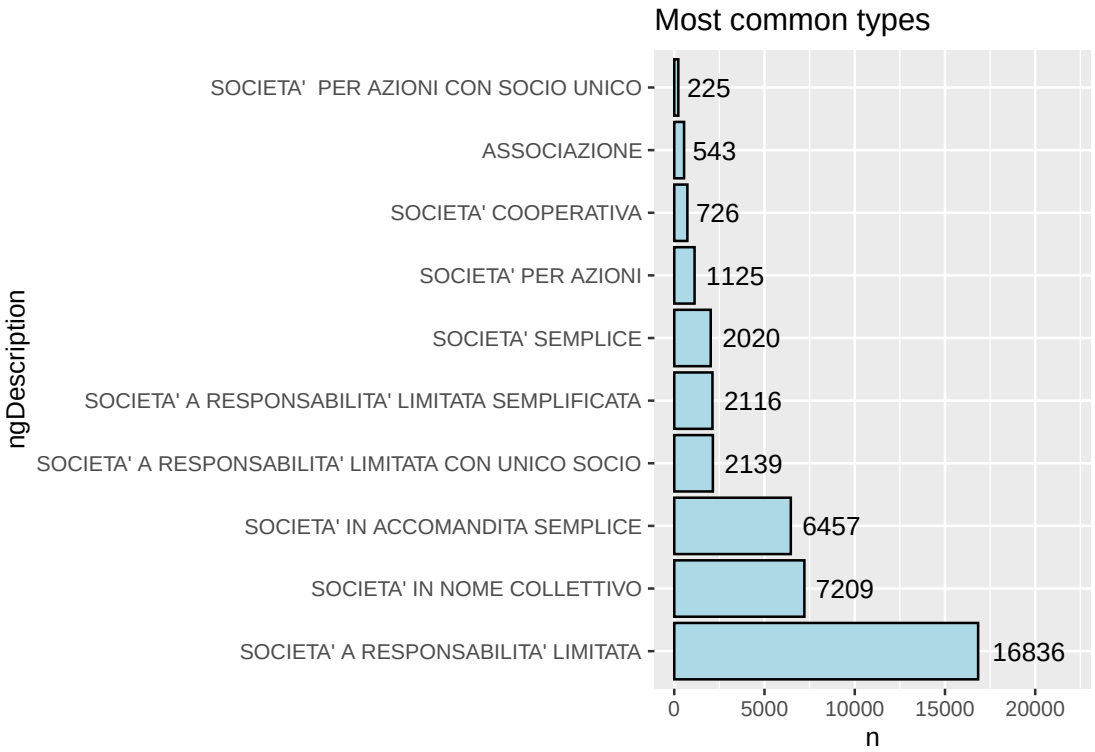
```
df <- companies2  %>% count(ng2)
print(paste("The dataset contains ", nrow(df), "types of companies."), quote=FALSE)
```

```
## [1] The dataset contains  34 types of companies.
```

```
df <- df %>% inner_join(types)
```

```
## Joining, by = "ng2"
```

```
df <- df  %>% arrange(-n)
df$ngDescription <- factor(df$ngDescription, levels = df$ngDescription) #lock facto
ggplot(data=head(df, 10), aes(x=ngDescription, y=n))  + geom_bar(stat="identity", c
```



dates, age of companies, years in business The dataset provides several dates: start of activity, dates of bankarupcy and cancellation We are interested in a broader information: "years in business"

Information on bankarupcy should be redundant, since non-active companies have been removed; nevertheless, past check showed unconistend data in the original tables. If bancarupcy dates are present, the company is considered as non-actie and removed.

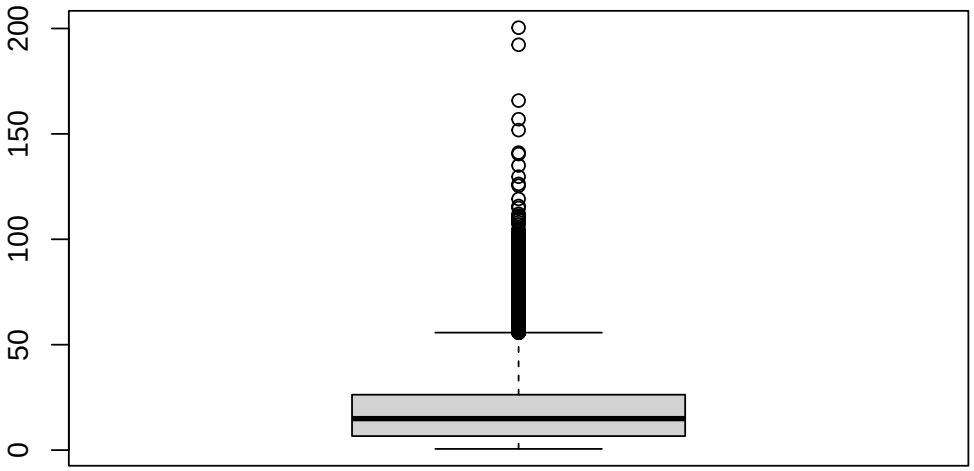
at the end we keep only eta; all data fields can be removed

```
dates <- companies %>% select(starts_with("data"))
tmp <- dates %>% summary(is.na())
tmp
```

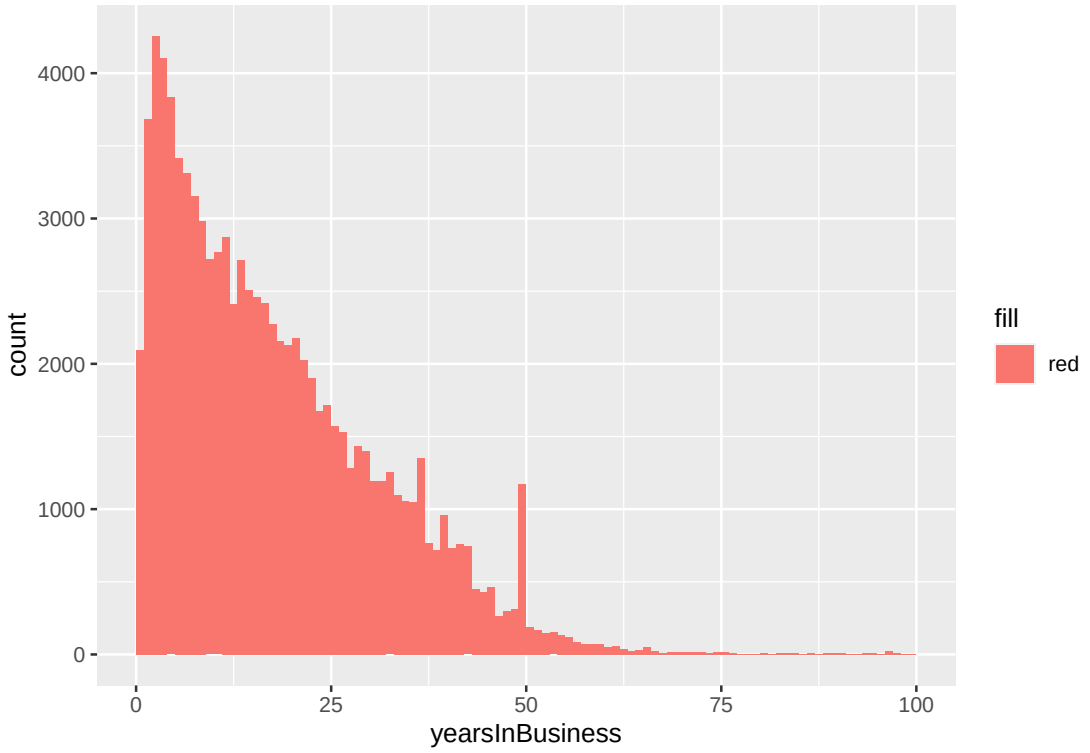
```
##    data_cost           data_isc_ri          data_isc_rd
##  Min.   :1807-01-01   Min.   :1996-02-08   Min.   :1856-04-26
##  1st Qu.:1992-12-23   1st Qu.:1996-12-23   1st Qu.:1996-12-11
##  Median :2005-01-02   Median :2007-06-19   Median :2007-05-31
```

```
##  Mean   :2002-02-04   Mean   :2007-04-23   Mean   :2005-01-09
##  3rd Qu.:2014-03-21   3rd Qu.:2015-10-09   3rd Qu.:2015-09-02
##  Max.   :2021-05-28   Max.   :2021-06-09   Max.   :2021-06-09
##  NA's   :54068        NA's   :1052         NA's   :5
##   data_isc_aa         data_canc       data_ini_at         data_cess_att
##  Min.   :1937-10-24   Mode:logical   Min.   :1821-10-05   Min.   :NA
##  1st Qu.:1997-10-20   NA's:93106     1st Qu.:1996-01-30   1st Qu.:NA
##  Median :2008-01-14                  Median :2007-04-03   Median :NA
##  Mean   :2005-04-10                  Mean   :2004-04-25   Mean   :NA
##  3rd Qu.:2015-12-15                  3rd Qu.:2015-07-07   3rd Qu.:NA
##  Max.   :2021-06-09                  Max.   :2105-02-28   Max.   :NA
##  NA's   :63054                       NA's   :1512         NA's   :93106
##    data_fall           data_liquid
##  Min.   :1982-10-01   Min.   :2009-06-15
##  1st Qu.:1997-02-04   1st Qu.:2010-12-25
##  Median :2003-09-24   Median :2012-10-08
##  Mean   :2003-06-12   Mean   :2013-11-12
##  3rd Qu.:2008-10-04   3rd Qu.:2014-09-30
##  Max.   :2021-05-18   Max.   :2019-12-20
##  NA's   :92530        NA's   :93089
```

```
companies <- companies %>% rowwise() %>%
            mutate(MinDate = min(data_isc_ri, data_isc_rd, data_isc_aa, data_ini_at,  na.rm=TR
            mutate(yearsInBusiness = as.numeric(as.Date("2022-01-01") - MinDate) / 365  )

tmp <- companies %>% select(starts_with("data")) %>% summary(is.na())

boxplot(companies$yearsInBusiness)
```




```
ggplot(data=companies, aes(x=yearsInBusiness, fill = "red")) + geom_histogram(break
```



TODO remove c(data_ini_at, data_cess_att, data_fall, data_liquid, data_cost, data_isc_ri, data_isc_rd,data_isc_aa,data_canc)

2.1.6 employees

addetti_aaaa, addetti_indip, addetti_dip

2.1.7 share capital

capitale, capitale_valuta

2.1.8 other attributes

TODO other attributes are relevant as signs of innovation imp_startup, imp_femminile, imp_giovanile, imp_straniera, imp_pmi, imp_sedi_ee, imp_eefvg
show distribution for each

```
companies$imp_pmi       <- as.factor(companies$imp_pmi)
companies$imp_startup   <- as.factor(companies$imp_startup)
companies$imp_giovanile <- as.factor(companies$imp_giovanile)
companies$imp_femminile <- as.factor(companies$imp_femminile)
companies$imp_straniera <- as.factor(companies$imp_straniera)
companies$imp_sedi_ee   <- as.factor(companies$imp_sedi_ee)
```

Now we can save clean data to csv

```
companies %>% write_csv(paste0(pathTidyData,"cmp.csv"),)
```

2.2 Codici

Each company is associated with a list of activity codes, according to NACE classification. The corresponding information is available in *t_codici.csv* . As in previous files, metadata can be inored at this stage. More info: Complete list of all NACE Code NACE (Nomenclature of Economic Activities) is the European statistical classification of economic activities. NACE groups organizations according to their business activities. [https://nacev2.com/en]

> TODO nace codes are associated with a company and each of its localizations. We may be interesed in reducin the compexity, summarizing all codes, and ignoring association to each location. But this can be an issue in some cases. For example a company has its head office in Rome, with some codes, and a local unit in Trieste engaged in different activities. Shall we consider all the codes, or by location? TODO Some companies have no nace codes associated: how many? should we drop the corresponding row in companies? TODO Explore code types (I P S) they are not unique.

3 Exploring dataset “bilanciFVG”

This section is dedicated to load and preprocess financial statement data for the dataset *imprese-fvg*. The relevant file is “_DATA/imprese-fvg/bilanci-fvg.csv”.

The relevant file is *bilanci-fvg.csv*. Each observation is a summary of balance sheet data (bsd) of a company (identified by *cf*) for a given year. Column labels need some improvement to remove whitespaces and possibly short english names.

```
bsd <- read_delim( paste0(pathRawData,"imprese/bilanci-fvg.csv") )
```

```
## Rows: 125617 Columns: 18
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ";"
## chr (16): cf, cia, Totale attivo, Totale Immobilizzazioni immateriali, Credi...
## dbl  (2): rea, anno
```

```
##
## i Use ‘spec()‘ to retrieve the full column specification for this data.
## i Specify the column types or set ‘show_col_types = FALSE‘ to quiet this message.
```

```
spec(bsd) # tydiverse for str(companies)
```

```
## cols(
##   cf = col_character(),
##   cia = col_character(),
##   rea = col_double(),
##   anno = col_double(),
##   ‘Totale attivo‘ = col_character(),
##   ‘Totale Immobilizzazioni immateriali‘ = col_character(),
##   ‘Crediti esigibili entro l’esercizio successivo‘ = col_character(),
##   ‘Totale patrimonio netto‘ = col_character(),
##   ‘Debiti esigibili entro l’esercizio successivo‘ = col_character(),
##   ‘Totale valore della produzione‘ = col_character(),
##   ‘Ricavi delle vendite‘ = col_character(),
```

```
##   `Totale Costi del Personale` = col_character(),
##   `Differenza tra valore e costi della produzione` = col_character(),
##   `Ammortamento Immobilizzazione Immateriali` = col_character(),
##   `Utile/perdita esercizio ultimi` = col_character(),
##   `valore aggiunto` = col_character(),
##   tot.aam.acc.svalutazioni = col_character(),
##   `(ron) reddito operativo netto` = col_character()
## )
```

```
bsd <- bsd %>%
        rename(year = anno) %>%
        rename(totEquity = `Totale patrimonio netto`) %>%
        rename(totAssets = `Totale attivo`) %>%
        rename(totIntang = `Totale Immobilizzazioni immateriali`) %>%
        rename(staffCost = `Totale Costi del Personale`) %>%
        rename(turnover  = `Ricavi delle vendite`) %>%
        select(cf,year,turnover, totAssets, totIntang, staffCost  )
```

```
bsd <- bsd %>%
  mutate(across(everything(), gsub, pattern = "[.]", replacement = "")) %>%
  mutate(across(everything(), gsub, pattern = ",", replacement = ".")) %>%
  mutate(across(.cols = 2:6, .fns = as.numeric))
```

```
bsd %>% write_csv(paste0(pathTidyData,"bsd.csv"))
```

There are 18 columns but in this project we will use only 4, namely "cf", "year", revenues" and "staff cost". Data should be loaded as string and then converted taking into account some issues with format of numerical variables.

To convert bsd*revenuesandbsd*staffcost to numbers, we need to remove the "." used as thousand separators, and replace "," with "." as a decimal separator.

We will focus the analysis on a list of companies that are tenats at Area Science Park. The list is available in the file "data/imprese-fvg/area-tenants.csv" so we can load it in al list ("filter") and use it to subset *bsd*.

```
tenants <- read_delim( paste0(pathRawData,"area-science-park/tenants.txt") ) %>%
  select(cf)
```

```
## New names:
## * `` -> ...7
```

```
## Rows: 68 Columns: 7
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ";"
## chr (6): insediati, Ente/Azienda, cf, DENOMINAZIONEiifvg, Campus, Addetti (b...
## lgl (1): ...7
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
tens = c(tenants$cf)
bsd_tenants <- bsd %>% subset(cf %in% tenants$cf) %>%
                mutate(cf = as.factor(cf)) %>% drop_na()
```

The variable bsd$revenues spans from 0 to 1e9, so it is more convenient to work with log10

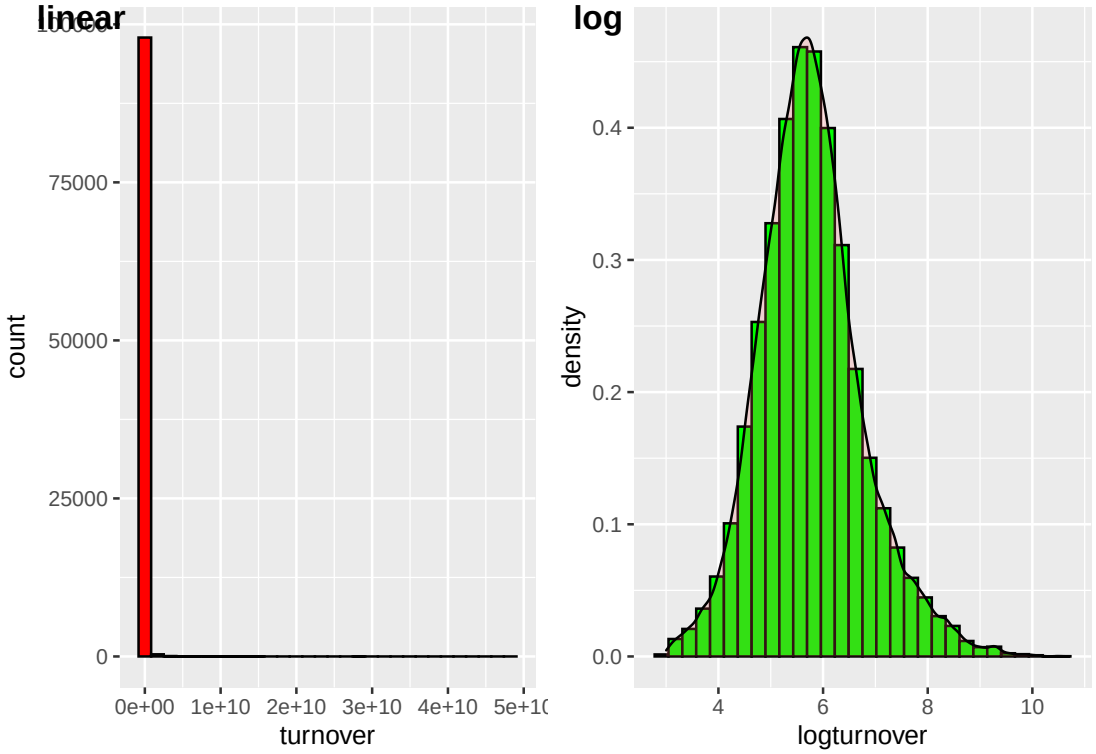
```
library(ggplot2)
library(ggpubr)
```

```
## Warning: il pacchetto 'ggpubr' è stato creato con R versione 4.1.2
```

```
bsd3 <- bsd %>% subset(turnover > 1000) %>% subset(year = 2019)
bsd3$logturnover <- log10(bsd3$turnover)
# hist(bsd$turnover)
# hist(bsd$logturnover)
h1 <- ggplot(bsd3, aes(x=turnover)) + geom_histogram(color="black", fill="red")
h2 <- ggplot(bsd3, aes(x=logturnover)) + geom_histogram(color="black", fill="green", aes(y=..c
figure <- ggarrange(h1, h2,labels = c("linear", "log"), ncol = 2, nrow = 1)
```

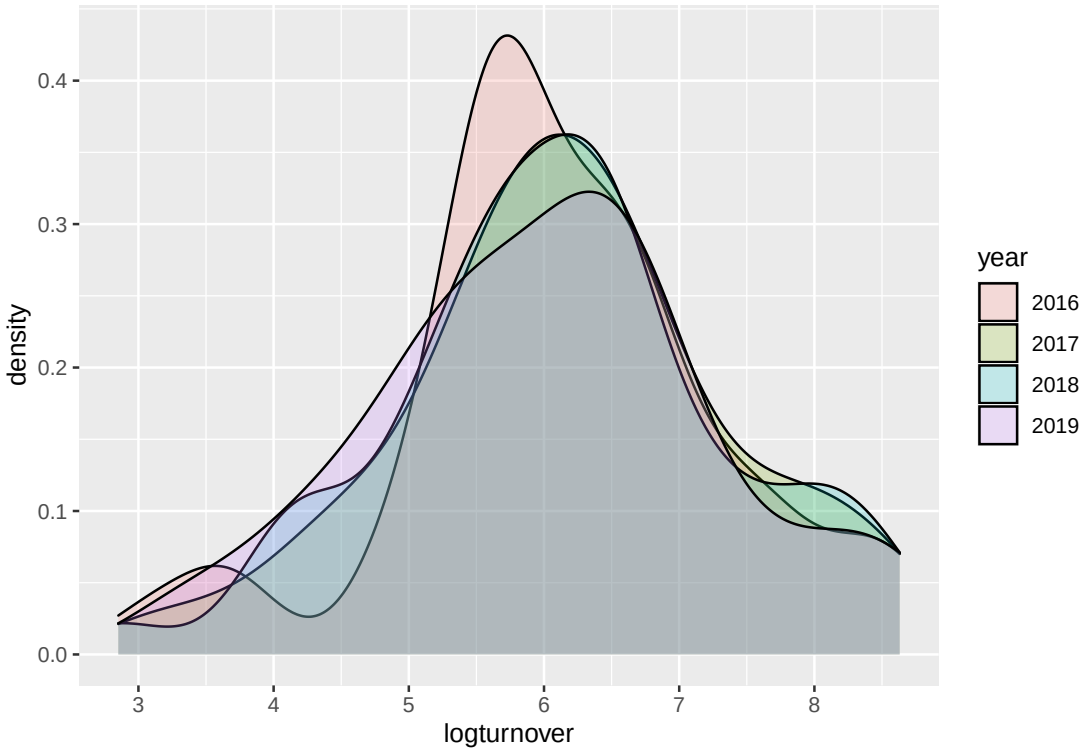
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
figure
```




```
bsd_tenants$logturnover <- log10(bsd_tenants$turnover)

tmp <- bsd_tenants  %>%
               subset(year >= 2016) %>%
               mutate(year = as.factor(year))

figure <- ggplot(tmp, aes(x=logturnover,fill=year)) + geom_density(alpha=.2)
figure
```

```
## Warning: Removed 10 rows containing non-finite values (stat_density).
```


density
0.4
0.3
0.2
0.1
0.0
3
4
5
6
7
8
logturnover
year
2016
2017
2018
2019

4 Exploring dataset CO-FVG

The original data is organized in 8 files: dati_2014.csv, dati_2015.csv, dati_2016.csv, dati_2017.csv, dati_2018.csv, dati_2019.csv, dati_2020.csv, dati_2021.csv. > TODO Currently, data exploration phase is focused on only one of the files above. Should extend it to all files using a for loop and appending results to a data.frame.

```
empl <- read_delim( paste0(pathRawData,"dati_2018.csv"))
```

```
## New names:
## * `` -> ...1
```

```
## Rows: 395456 Columns: 43
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: "|"
## chr  (25): CF, az_ragione_soc, genere, id_cittadino, professione, qualifica,...
## dbl   (8): ...1, anno, eta, mese, saldo, codice_istat, SLL_codice, qualifica...
## lgl   (5): somm, erroriEta, errori_qualifica, erroriCF, errori
## date  (5): data, data_fine, data_fine_prev, data_inizio, data_nascita
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

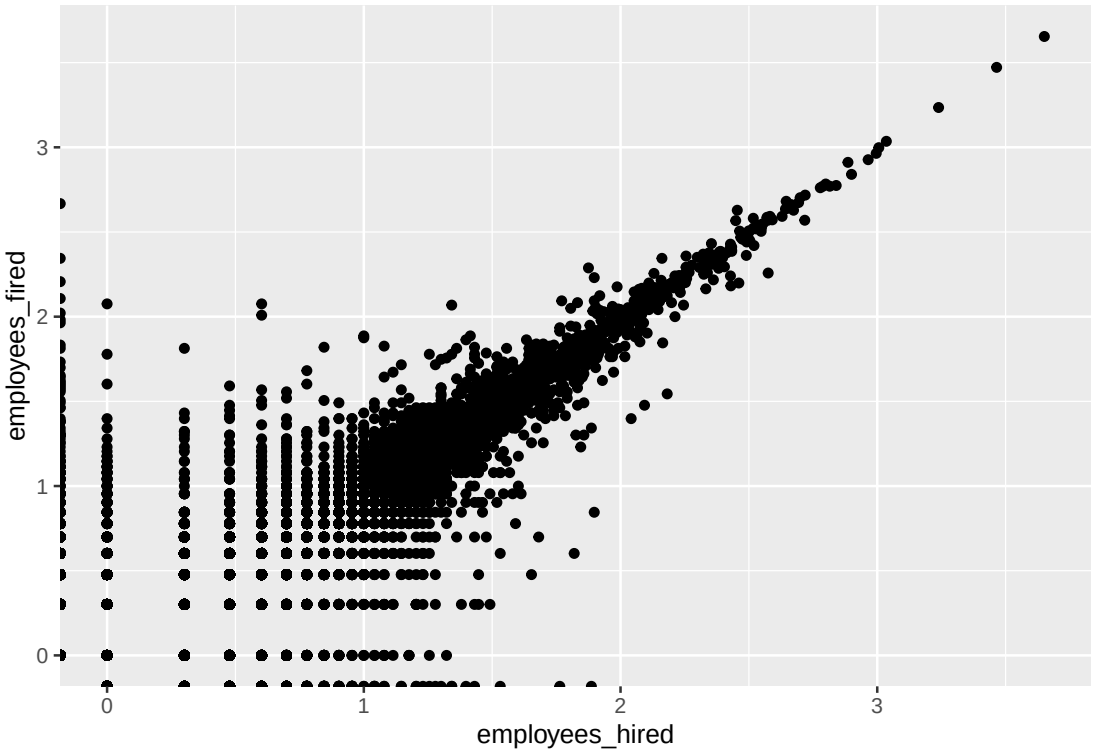
```
features <-names(empl)
some_features <- c("CF","anno","eta","genere","iso3","professione","qualifica","saldo")
```

There are 43 features available: ...1, CF, anno, az_ragione_soc, data, data_fine, data_fine_prev, data_inizio, data_nascita, eta, genere, id_cittadino, mese, professione, qualifica, qualifica_codice, rl_ateco, rl_ateco_macro, rl_ateco_settore, saldo, sede_op_ateco, sede_op_comune, sede_op_indirizzo, sede_op_provincia, somm, tipo_contratto, tipo_orario, cittadinanza, iso3, contientne, aggregazione, provincia, sigla_prov, comune_istat, codice_istat, SLL_codice, SLL_nome, contratto, erroriEta, errori_qualifica, qualifica_2_digit, erroriCF, errori. For the purpose of data exploration we will focus only on the following: CF, anno, eta, genere, iso3, professione, qualifica, saldo.

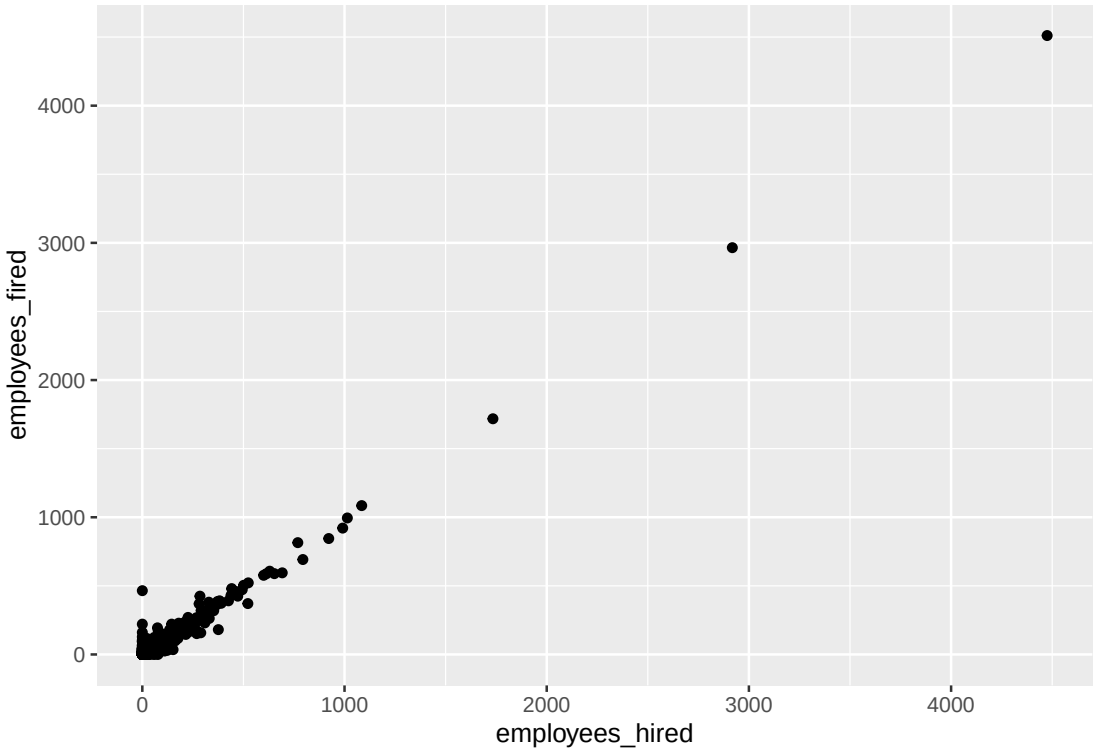
```
empl <- empl %>%
  select( one_of(some_features) ) %>%
  rename( year = anno)

empl_flows <- empl %>% select( c(CF, saldo, year)) %>%
  mutate(hf = factor(saldo))%>%
  mutate(hf=recode(hf,`-1`="fired",`1`="hired"))%>%
  group_by(CF,hf, year) %>%
  summarize(hiredfired=  sum(saldo) ) %>%
  pivot_wider( names_from = hf, values_from = hiredfired) %>%
  replace(is.na(.), 0) %>%
  mutate(turnover = hired-fired) %>%
  mutate(net = hired+fired)
```

```
## `summarise()` has grouped output by 'CF', 'hf'. You can override using the `.gro
```

```
employees_hired = log10(empl_flows$hired)
employees_fired=  log10(-empl_flows$fired)
ggplot(empl_flows, aes(x=employees_hired, y=employees_fired))+
    geom_point()
```



```
employees_hired = (empl_flows$hired)
employees_fired=  (-empl_flows$fired)
ggplot(empl_flows, aes(x=employees_hired, y=employees_fired))+
    geom_point()
```



> TODO import, calculate net saldo and turnover, divide companies in quartiles

TODO improve formatting tables with library(kableExtra) %>% kable()

```
empl_flows %>% write_csv(paste0(pathTidyData,"empl_flows.csv"),)
```