Dvojrozmerny datovy subor, korelacna analyza Analyzujeme dvojrozmerny datovy subor. Ratame charakteristiky pre jednorozmerne subory, pribudnu charakteristiky pre dvojrozmerny subor. Priklad. Tabulka uvadza cenu pevnych diskov (y) ich kapacitu (x) od vyrobcu ABC. Zratajte vektor strednych hodnot a disperzii. x <- c(160, 250, 320, 500, 750, 900, 1000, 1500, 2000) y <- c(789, 800, 851, 874, 1193, 1200, 1335, 1704, 2073) c(mean(x), mean(y))## [1] 820.000 1202**.**111 c(var(x), var(y)) ## [1] 376425.0 198922.1 Dalej ratame charakteristiku dvojrozmerneho datoveho suboru kovarianciu (Personova, Kendallova, Spearmanova). Je to cislo, ktore nam charakterizuje, ci je medzi zlozkami linearna zavislost alebo nie, ci koreluju. Kym neznormujeme toto cislo, tak mozeme povedat iba jedine, cov = 0 zlozky su nekorelovanea ako cov != 0 su korelovane. plot(x, y, type = 'b')1600 1200 500 1000 1500 2000 cov(x, y) #korelovane cov(x, y, method = 'kendall') ## [1] 72 cov(x, y, method = 'spearman') ## [1] 7.5 Aby sme zistili, ako silno sa ovplyvnuju, je potrebne nromovat kovarianciu, dostaneme korelacny koeficient, co je cislo medzi -1 a 1. Blizke -1, 1 silna, silna korelacia, silna linearna zavislost. Blizke 0, nekorelovane a linearne nezavisle iba pre normalne rozdelene data. Zlozitejsie zavislosti sa nemusia odhalit. Pearsonov korelacny koeficient je citlivy na vybocujuce hodnoty, vsetky naraz ratat. Pripravime funkciu korelacie. cor(x, y) ## [1] 0.9938807 korelacie <- function(x, y) {c('Pearson' = cor(x, y),</pre> 'Kendall' = cor(x, y, method = 'kendall'), 'Spearman' = cor(x, y, method = 'spearman'))} korelacie(x, y) ## Pearson Kendall Spearman ## 0.9938807 1.0000000 1.0000000 Testovat korelacny koeficient mozeme, dvojrozmerne data ale musia byt normalne rozdelene, testujeme hypotezu o nulovosti korelacneho koeficientu. $H_0 \quad
ho = 0 \quad H_1 \quad
ho
eq 0$ kniznice pre test normality library(nortest) library (mvnormtest) uprava dat, dvojrozmerny subor data <- rbind(x, y)</pre> mshapiro.test(data) ## Shapiro-Wilk normality test ## data: Z ## W = 0.86547, p-value = 0.1099 P hodnota > 0.05 nezamietam hypotezu o normalite dat mozeme testovat nulovost korelacneho koeficienta cor.test(x, y) #zamietam H0 ## Pearson's product-moment correlation ## ## data: x and y ## t = 23.806, df = 7, p-value = 5.867e-08 ## alternative hypothesis: true correlation is not equal to 0 ## 95 percent confidence interval: ## 0.9700441 0.9987619 ## sample estimates: ## 0.9938807 cor.test(x, y, method = 'kendall') #zamietam HO ## Kendall's rank correlation tau ## ## data: x and y ## T = 36, p-value = 5.511e-06 ## alternative hypothesis: true tau is not equal to 0 ## sample estimates: ## tau ## 1 cor.test(x, y, method = 'spearman') #zamietam HO ## Spearman's rank correlation rho ## ## data: x and y ## S = 0, p-value = 5.511e-06## alternative hypothesis: true rho is not equal to 0 ## sample estimates: ## rho ## 1 graf s viac informaciami, nacitame kniznice library(ggplot2) library(ggpubr) ## Warning: package 'ggpubr' was built under R version 4.2.3 data1 <- data.frame(x, y)</pre> ggscatter(data1, 'x', 'y', add = 'reg.line', conf.int = T, cor.coef = T)R = 0.99, p = 5.9e-082000 -1500 1000 1500 1000 2000 500 Nasiumulujeme linearne nezavisle, linearne zavisle a data so zlozitejsou zavislostou, grafy a korelacne koeficienty xx <- rnorm(100, 2, 4)yy < - rnorm(100, 1, 1)plot(xx, yy, main = 'Nezavisle data') Nezavisle data 2 \leq 0 7 -5 -10 -5 0 5 10 XX korelacie(xx, yy) ## Pearson Kendall Spearman ## 0.1788016 0.1034343 0.1647165 xxx <- 1:100+xx yyy < -2+3*xxx+rnorm(100, 2, 6)plot(xxx, yyy, main = 'Zavisle data') Zavisle data 100 50 0 0 60 80 20 40 100 XXX korelacie(xxx, yyy) ## Pearson Kendall Spearman ## 0.9977918 0.9567677 0.9966637 x1 <- 1:100 $y1 < -\sin(x1) + rnorm(100, 0, 0.05)$ plot(x1, y1, main='Sin(x)', type = 'b')Sin(x) 0.5 0.0 -0.5 -1.0 20 40 60 80 100 **x**1 korelacie(x1, y1) Kendall Spearman Pearson ## -0.03782328 -0.02101010 -0.02945095 Korelacna analyza pre viacrozmerny vektor Castejsie mame viacrozmerne merania, vtedy ratame korelacne koeficienty vzdy medzi dvomi zlozkami, zapisujeme do matice, ktora sa nazyva korelacna matica. Symetricka matica, na diagonale su jednotky. Vyukovy dataset mtcars, carData, car library(carData) library(car) head(mtcars) ## mpg cyl disp hp drat wt qsec vs am gear carb ## Mazda RX4 21.0 6 160 110 3.90 2.620 16.46 0 1 4 21.0 6 160 110 3.90 2.875 17.02 0 1 ## Mazda RX4 Wag ## Datsun 710 22.8 4 108 93 3.85 2.320 18.61 1 1 ## Hornet 4 Drive 21.4 6 258 110 3.08 3.215 19.44 1 0 ## Hornet Sportabout 18.7 8 360 175 3.15 3.440 17.02 0 0 ## Valiant 18.1 6 225 105 2.76 3.460 20.22 1 0 View(cor(mtcars)) lepsie je to aj vizualizovat, kniznica corrplot library(corrplot) ## Warning: package 'corrplot' was built under R version 4.2.3 ## corrplot 0.92 loaded km <- cor(mtcars)</pre> corrplot(km) 0.6 0.4 0.2 0 -0.2 -0.4 -0.6 -0.8 corrplot.mixed(km) - 0.4 -0.78 0.83 0.79 hp 0.2 0.68 -0.70 -0.71 -0.45 drat |-0.87 | 0.78 | 0.89 | 0.66 |-0.71 | wt 0 0.42 -0.59 -0.43 -0.71 0.09 -0.17 qsec -0.2 0.66 -0.81 -0.71 -0.72 | 0.44 -0.55 | 0.74 | vs -0.4 0.60 -0.52 -0.59 -0.24 | 0.71 -0.69 -0.23 | 0.17 -0.6 0.70 -0.58 -0.21 0.21 0.79 gear 0.48 -0.49 -0.56 --0.8 **-0.55** | 0.53 | 0.39 | 0.75 | 0.09 | 0.43 | -0.66 | -0.57 | 0.27 carb Testovat korelacne koeficienty mozno aj naraz Hmisc library(Hmisc) ## Loading required package: lattice ## Loading required package: survival ## Loading required package: Formula ## Attaching package: 'Hmisc' ## The following objects are masked from 'package:base': ## format.pval, units rcorr(as.matrix(mtcars)) mpg cyl disp hp drat wt qsec vs am gear carb ## mpg 1.00 -0.85 -0.85 -0.78 0.68 -0.87 0.42 0.66 0.60 0.48 -0.55 ## cyl -0.85 1.00 0.90 0.83 -0.70 0.78 -0.59 -0.81 -0.52 -0.49 0.53 ## disp -0.85 0.90 1.00 0.79 -0.71 0.89 -0.43 -0.71 -0.59 -0.56 0.39 ## hp -0.78 0.83 0.79 1.00 -0.45 0.66 -0.71 -0.72 -0.24 -0.13 0.75 ## drat 0.68 -0.70 -0.71 -0.45 1.00 -0.71 0.09 0.44 0.71 0.70 -0.09 ## wt -0.87 0.78 0.89 0.66 -0.71 1.00 -0.17 -0.55 -0.69 -0.58 0.43 ## qsec 0.42 -0.59 -0.43 -0.71 0.09 -0.17 1.00 0.74 -0.23 -0.21 -0.66 ## vs 0.66 -0.81 -0.71 -0.72 0.44 -0.55 0.74 1.00 0.17 0.21 -0.57 ## am 0.60 -0.52 -0.59 -0.24 0.71 -0.69 -0.23 0.17 1.00 0.79 0.06 ## gear 0.48 -0.49 -0.56 -0.13 0.70 -0.58 -0.21 0.21 0.79 1.00 0.27 ## carb -0.55 0.53 0.39 0.75 -0.09 0.43 -0.66 -0.57 0.06 0.27 1.00 ## ## n= 32## ## P mpg cyl disp hp drat wt qsec vs am gear 0.0000 0.0000 0.0000 0.0000 0.0000 0.0171 0.0000 0.0003 0.0054 0.0000 0.0000 0.0000 0.0000 0.0004 0.0000 0.0022 0.0042 ## cyl 0.0000 ## disp 0.0000 0.0000 0.0000 0.0000 0.0131 0.0000 0.0010 ## hp 0.0000 0.0000 0.0000 0.0100 0.0000 0.0000 0.0000 0.1798 0.4930 ## drat 0.0000 0.0000 0.0000 0.0100 0.0000 0.6196 0.0117 0.0000 0.0000 ## wt 0.0000 0.0000 0.0000 0.0000 0.0000 0.3389 0.0010 0.0000 0.0005 ## qsec 0.0171 0.0004 0.0131 0.0000 0.6196 0.3389 0.0000 0.2057 0.2425 ## vs 0.0000 0.0000 0.0000 0.0117 0.0010 0.0000 0.3570 0.2579 ## am 0.0003 0.0022 0.0004 0.1798 0.0000 0.0000 0.2057 0.3570 0.0000 ## gear 0.0054 0.0042 0.0010 0.4930 0.0000 0.0005 0.2425 0.2579 0.0000 ## carb 0.0011 0.0019 0.0253 0.0000 0.6212 0.0146 0.0000 0.0007 0.7545 0.1290 ## mpg 0.0011 ## cyl 0.0019 ## disp 0.0253 ## hp 0.0000 ## drat 0.6212 ## wt 0.0146 ## qsec 0.0000 ## vs 0.0007 ## am 0.7545 ## gear 0.1290 ## carb Este jedna vhodna kniznica library(correlation) ## Warning: package 'correlation' was built under R version 4.2.3 correlation(data1) ## # Correlation Matrix (pearson-method) ## Parameter1 | Parameter2 | r | 95% CI | t(7) | p ## -----## x | y | 0.99 | [0.97, 1.00] | 23.81 | < .001*** ## p-value adjustment method: Holm (1979) ## Observations: 9 Grafy, ktore nam umoznia zistit strukturu dat, zavislosti v datach Nase data dataE.xlsx library(readxl) data <- read_xlsx('dataE.xlsx')</pre> head(data) ## # A tibble: 6 × 13 ## respon...¹ pohla...² vek vzdel...³ stav fajciar praca clen mprij mstrava rdovo...⁴ ## 1 1 m 28 3 1 0 2 5 1500 250 10000 ## 2 2 m 22 2 1 0 1 4 900 200 350 ## 3 3 m 50 1 2 0 2 4 975 350 300 ## 4 4 z 39 2 2 0 3 5 1200 400 500 ## 5 5 z 53 3 2 0 1 5 1800 400 15000 ## 6 6 z 55 1 3 0 3 2 825 200 200 ## # ... with 2 more variables: pocit <dbl>, invest <dbl>, and abbreviated variable ## # names 'respondent, 'pohlavie, 'vzdelanie, 'rdovolenka pairs(data[,c('vek', 'mprij', 'mstrava')]) 600 1000 1400 1800 vek mprij mstrava 50 60 100 150 200 250 300 350 400 30 40 korelacie(data\$mprij, data\$mstrava) ## Pearson Kendall Spearman ## 0.7276575 0.6340417 0.7882542 pairs(data[,c('vek', 'mprij', 'mstrava')], col='orange') 600 1000 1400 vek mprij mstrava 50 100 150 200 250 300 350 400 30 40 library(GGally) ## Warning: package 'GGally' was built under R version 4.2.3 ## Registered S3 method overwritten by 'GGally': ## method from ## +.gg ggplot2 ## Attaching package: 'GGally' ## The following object is masked from 'package:latexpdf': ## ## wrap ggpairs(data[,c('vek', 'mprij', 'mstrava')]) mstrava 0.03 -0.02 -Corr: Corr: 0.180 0.351* 0.01 0.00 -2000 -1500 Corr: 0.728*** 1000 400 -300 -200 -100 - • 1500 2000100 200 toto boli graficke analyzy pre cely datovy subor Mozeme analyzovat aj podmnoziny datoveho suboru ggpairs(data[,c('pohlavie', 'vek', 'mprij', 'mstrava')], aes(colour=pohlavie, alpha = 0.3)) ## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`. ## `stat bin()` using `bins = 30`. Pick better value with `binwidth`. ## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`. 25 -20 -15 -10 -60 -Corr: 0.180 Corr: 0.351* 50 m: 0.201 m: 0.475* z: 0.115 z: 0.205 1500 m: 0.537** 1000 z: 0.852*** 400 -300 -200 -200 1500 300 1000 200000 Regresna analyza Ked korelacne koeficienty su vysoke, teda data su linearne zavisle, tak nasleduje regresna analyza. Snazime sa zavislost popisat vhodnou funkciou - regresna funkcia, priklad zo zaciatku, prelozime priamku y=a+bx plot(x, y, type = 'b')1600 800 500 1000 1500 2000 lr1 <- lm(y~x) lr1 ## ## Call: ## $lm(formula = y \sim x)$ ## Coefficients: ## (Intercept) ## 609.6629 0.7225 summary(lr1) $## lm(formula = y \sim x)$ ## Residuals: ## Min 1Q Median 3Q Max ## -96.912 2.839 10.138 18.341 63.737 ## Coefficients: Estimate Std. Error t value Pr(>|t|) ## (Intercept) 609.66288 30.45571 20.02 1.94e-07 *** 0.72250 0.03035 23.81 5.87e-08 *** ## ---## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ## Residual standard error: 52.67 on 7 degrees of freedom ## Multiple R-squared: 0.9878, Adjusted R-squared: 0.9861 ## F-statistic: 566.7 on 1 and 7 DF, p-value: 5.867e-08 Multiple R-squared -> cim blizsie k 1, tym lepsi model -> 98% dat je vysvetlenych nasou priamkou #abline(lr1, col = 'red') Ak konstantu neuvazujeme lr2 <- lm(y~0+x)summary(lr2) ## ## Call: $\#\# lm(formula = y \sim 0 + x)$ ## Residuals: ## Min 1Q Median 3Q Max ## -364.9 103.0 264.5 460.9 594.0 ## Coefficients: ## Estimate Std. Error t value Pr(>|t|) ## x 1.2189 0.1249 9.76 1.02e-05 *** ## ---## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ## Residual standard error: 376 on 8 degrees of freedom ## Multiple R-squared: 0.9225, Adjusted R-squared: 0.9128 ## F-statistic: 95.26 on 1 and 8 DF, p-value: 1.017e-05 #abline(lr2, col = 'green') prelozime kvadraticku funckiu

 $lr3 <- lm(y\sim poly(x, 2))$

$lm(formula = y \sim poly(x, 2))$

Min 1Q Median 3Q Max ## -91.634 -12.870 2.168 25.098 58.875

#lines(x, fitted(lr3), col = 'blue')

Estimate Std. Error t value Pr(>|t|)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 52.08 on 6 degrees of freedom
Multiple R-squared: 0.9898, Adjusted R-squared: 0.9864
F-statistic: 290.3 on 2 and 6 DF, p-value: 1.07e-06

17.36 69.241 6.11e-10 ***

52.08 1.076 0.323

52.08 24.072 3.38e-07 ***

summary(1r3)

Residuals:

Coefficients:

(Intercept) 1202.11

poly(x, 2)1 1253.78

poly(x, 2)2 56.04

##

Call:

cv9.R

2023-04-13

library(latexpdf)

Marek