library(tidyverse) library(MASS) ############# # Task 9 ############# # (a) m=30n=12 p = 0.7x<-rbinom(n=m,size=n,prob=p)</pre> # (b) freq.table=table(x) # freq.table is of class "table" observed.vals=as.numeric(names(freq.table)) # add all possible values (not just observed values) to the vector plot.vals=0:max(observed.vals) comb.table=matrix(0,2,length(plot.vals)) colnames(comb.table)=plot.vals rownames(comb.table)=c("sample",sprintf("Binom(%2.1i, %2.1f) pmf",n, p)) # compute proportions for the observed values comb.table[1,observed.vals+1]=freq.table/m # compute probabilities for all possible values comb.table[2,]=dbinom(plot.vals,size=n,prob=p) barplot(comb.table,beside=TRUE,col=c("blue","red"),ylab="relative frequency / probability",xlab="value",legend.text=TRUE,args.legend=list(x="topleft")) # (C) x.bar=mean(x)s2=var(x)title(main = $sprintf("mean=%2.1f - s^2=%2.1f", x.bar, s2))$ $T_mnp=sqrt(m)*((x.bar-n*p)/sqrt(n*p*(1-p)))$ print(T_mnp) # (d) calc.T<-function(m, n, p){</pre> x<-rbinom(n=m,size=n, prob=p)</pre> x.bar=mean(x)s2=var(x) $T_mnp=sqrt(m)*((x.bar-n*p)/sqrt(n*p*(1-p)))$ return(T_mnp) # (e) k=10000 m.vec=c(5,30,500)size=12 prob = 0.7z = seq(-4,4,0.01)for(m in m.vec){ T.vec=c()for(i in 1:k){ T.vec=c(T.vec,calc.T(m,n,p)) hist(T.vec,nclass=16,freq=FALSE) lines(z,dnorm(z),col="red",lty=3) ############# # Task 10 ############## # (a) solar = read.csv2("Solar.csv", stringsAsFactors = TRUE) solar\$batch = as.factor(solar\$batch) # (b) # create a scatterplot matrix using an argument of class formula pairs(~Pmax+Imax+Umax+Isc+Uoc,data=solar,col=c("red","blue","green","orange")[solar\$batch]) # (C) # create a boxplot using an argument of class formula boxplot(Uoc~batch, data=solar,xaxt="n",main="Boxplot for Uoc") axis(1, at=1:4)# alternative using the package ggplot2 ggplot(solar)+geom_boxplot(aes(Uoc, col=batch)) # (d) plot(solar\$Pmax,solar\$Isc,col=c("red","blue","green","orange")[solar\$batch]) legend(x="topleft", legend = levels(solar\$batch), col=c("red","blue", "green", "orange"), pch=1) X = solar\$Pmax[!is.na(solar\$Isc)] Y = solar\$Isc[!is.na(solar\$Isc)] # see Example I.4.6 and Theorem I.4.9 B = cbind(rep(1, length(X)), X) # alternatively cbind(1, X) reg.par.mat = ginv(B)%*%Y # (ii) reg = lm(Y~X)reg.par.lm = reg\$coef # comparison of the fitted parameters reg.par.mat reg.par.lm abline(reg.par.lm,col="black") # (e) # batch 1 X.1 = solar\$Pmax[!is.na(solar\$Isc)&solar\$batch=="1"] Y.1 = solar\$Isc[!is.na(solar\$Isc)&solar\$batch=="1"] reg1 = lm(Y.1~X.1)reg.par1= reg1\$coefficients abline(reg.par1,col="red") # batch 4 X.4 = solar\$Pmax[!is.na(solar\$Isc)&solar\$batch=="4"] Y.4 = solar\$Isc[!is.na(solar\$Isc)&solar\$batch=="4"] reg4 = lm(Y.4~X.4)reg.par4= reg4\$coefficients abline(reg.par4,col="orange") # alternative using the package ggplot2 ggplot(solar)+geom_point(aes(Pmax,Isc,col=batch))+geom_abline(aes(intercept=reg.par.lm[2]))+geom_abline(aes(intercept=reg.par.lm[2]),col="red")+geom_abline(aes(intercept=reg.par.lm[2]),slope=reg.par.lm[2]),col="red")+geom_abline(aes(intercept=reg.par.lm[2]),slope=reg.par.lm[2]),slope=reg.par.lm[2]),col="red")+geom_abline(aes(intercept=reg.par.lm[2]),slope=reg.par.lm[2]),slope=reg.par.lm[2]),slope=reg.par.lm[2]),col="red")+geom_abline(aes(intercept=reg.par.lm[2]),slope=reg.par.lm[2]),slop .par4[2]),col="orange")+scale_color_manual(values=c("red", "blue", "green", "orange")) # (f) solar\$Isc = round(ifelse(is.na(solar\$Isc),predict(reg,newdata=data.frame(X=solar\$Pmax)),solar\$Isc), digits=3) # alternative using the package dplyr solar %>% mutate(Isc=round(ifelse(is.na(Isc),predict(reg,newdata=data.frame(X=solar\$Pmax)),Isc),digits=3) # (g) save(solar,file="Solar.RData") ############# # Task 11 ############# rent.data = read.csv2("rent.csv", stringsAsFactors = TRUE) # (b) plot(rent.data\$space,rent.data\$rent.sqm) rent.lm1 = lm(rent.sqm~space,data=rent.data) abline(rent.lm1,col="red") # the simple linear regression obviously does not capture the structure behind the data # => transform the data points to find a better model # the scatterplot is similar to a plot of f(x)=1/x# => use the reciprocal of space instead: plot(1/rent.data\$space,rent.data\$rent.sqm) # we can see a clear linear structure and model it now using a linear regression # (C) rent.lm2 = lm(rent.sqm~I(1/space),data=rent.data) # the operator / is used in "formula" to construct the design matrix of complex models # => the formula rent.sqm~1/space is identical to rent.sqm~1 # Use the function I if you want to use an expression of a variable, e.g. 1/space, as predictor # here this leads to the predictor I(1/space) abline(rent.lm2,col="red") # the linear model with the predictor 1/space plot(rent.data\$space,rent.data\$rent.sqm) abline(rent.lm1,col="red") curve(rent.lm2\$coefficients[1]+rent.lm2\$coefficients[2]/x,col="blue",add=TRUE) # the new regression has a clearly better fit ############## # Task 12 ############# cars.data=read.table(file="cars2.dat",header=TRUE,stringsAsFactors = TRUE) speed=cars.data\$speed dist=cars.data\$dist # (b) plot(speed,dist) # (C) cars.lm1 = lm(dist ~ speed+I(speed^2)) # Similar to task 11: # the operators ^ and ** are used in "formula" to construct the design matrix of complex models # => the formula dist ~ speed+speed^2 is identical to dist ~ speed # Use the function I if you want to use an expression of a variable, e.g. speed^2, as predictor # here this leads to the predictor speed+I(speed^2) par = cars.lm1\$coefficients # curve interprets the first argument as function of "x" and can evaluate it curve(par[1]+par[2]*x+par[3]*x*x,col="red",add=TRUE) # alternative solution # better use the following way - it is numerically more stable because orthogonal polynomials are used cars.lm2 = lm(dist ~ poly(speed, degree = 2)) # Notice that the parameters are quite different: cars.lm1\$coefficients cars.lm2\$coefficients # Hence, we cannot simply plug the coefficients of cars.lm2 in a polynomial of degree 2 # Use the function predict: speed.grid = seq(min(speed), max(speed), length.out = 100) y.pred = data.frame(speed=speed.grid) # artificial data set with the same predictor variable as cars.lm2 y = predict(cars.lm2,newdata=y.pred) plot(speed,dist) lines(speed.grid,y,col="blue") # (d) alpha = 0.05Y = distr = 3r0 = 2n = 50B0 = cbind(1, speed)

B = cbind(B0, speed^2)

print(reject)

Q = B%*%solve(t(B)%*%B,t(B))

Bonus: Alternatives in (d)

reject.alt = p.value < alpha</pre>

compute the p-value:

use R functionality

anova(cars.lm3,cars.lm2)

print(reject.alt)

summary(cars.lm1)
summary(cars.lm2)

Q0 = B0%*solve(t(B0)%*8B0,t(B0))

numerator = Y % * % (Q-Q0) % * % Y/(r-r0)

F.statistic = numerator/denominator

(p.value <- 1-pf(F.statistic,1,47))</pre>

cars.lm3 = lm(dist ~ poly(speed, degree = 1))

Note the difference and pay attention if using the results given in summary

denominator = Y%*%(diag(50)-Q)%*%Y/(n-r)

reject = F.statistic > qf(1-alpha,1,47)