Regression in R

load useful packages for formatting output

```
library( pander ) # translate output to HTML / latex
library( magrittr ) # use the pipe operator %>%
library( knitr ) # kable function formats tables
```

create a toy dataset

```
x1 <- 1:100
x2 <- -0.1*x1 + rnorm(100)
x3 <- 0.05*x2 + rnorm(100)
y \leftarrow 2*x1 + 10*rnorm(100) + 10*x2
dat <- data.frame( y, x1, x2, x3 )</pre>
head( dat )
##
              y x1
                           x2
                                       xЗ
## 1 6.489172 1 0.6132310 0.53043802
## 2 -35.774792 2 -3.1351324 0.82019800
## 3 29.058439 3 0.6588230 -1.19311475
## 4 11.477368 4 -0.3853383 -0.04353684
## 5 -17.965633 5 -2.0930484 -1.22033111
## 6 31.777646 6 1.3981708 1.19573860
```

descriptive statistics

summary(dat) %>% kable

У	x1	x2	x3
Min. :-35.77	Min.: 1.00	Min. :-11.271	Min. :-2.4455
1st Qu.: 32.45	1st Qu.: 25.75	1st Qu.: -7.751	1st Qu.:-1.0294
Median: 49.87	Median: 50.50	Median: -4.949	Median: -0.3405
Mean: 52.55	Mean: 50.50	Mean : -4.958	Mean :- 0.2958
3rd Qu.: 74.95	3rd Qu.: 75.25	3rd Qu.: -2.665	3rd Qu.: 0.5513
Max. $:120.34$	Max. $:100.00$	Max. : 1.398	Max. : 2.0431

library(pastecs) # convenient descriptives function

stat.desc(dat) %>% t %>% round(2) %>% pander

Table 2: Table continues below

	nbr.val	nbr.null	nbr.na	min	max	range	sum
y	100	0	0	-35.77	120.3	156.1	5255
x1	100	0	0	1	100	99	5050
$\mathbf{x2}$	100	0	0	-11.27	1.4	12.67	-495.8
x3	100	0	0	-2.45	2.04	4.49	-29.58

	median	mean	SE.mean	CI.mean.0.95	var	std.dev	coef.var
y	49.87	52.55	3.19	6.33	1018	31.91	0.61
x1	50.5	50.5	2.9	5.76	841.7	29.01	0.57
x2	-4.95	-4.96	0.32	0.63	9.95	3.15	-0.64
x3	-0.34	-0.3	0.1	0.2	0.97	0.99	-3.34

grab only the desired descriptives

stat.desc(dat)[c(1,4,5,8,9,13),] %>% t %>% kable(format="markdown", digits=3)

	nbr.val	\min	max	median	mean	std.dev
у	100	-35.775	120.339	49.872	52.548	31.909
x1	100	1.000	100.000	50.500	50.500	29.011
x2	100	-11.271	1.398	-4.949	-4.958	3.155
x3	100	-2.445	2.043	-0.340	-0.296	0.987

stat.desc(dat)[c(1,4,5,8,9,13),] %>% t %>% pander(digits=3)

	nbr.val	min	max	median	mean	std.dev
\mathbf{y}	100	-35.8	120	49.9	52.5	31.9
$\mathbf{x1}$	100	1	100	50.5	50.5	29
x2	100	-11.3	1.4	-4.95	-4.96	3.15

	nbr.val	min	max	median	mean	std.dev
x 3	100	-2.45	2.04	-0.34	-0.296	0.987

copy and paste a table to excel

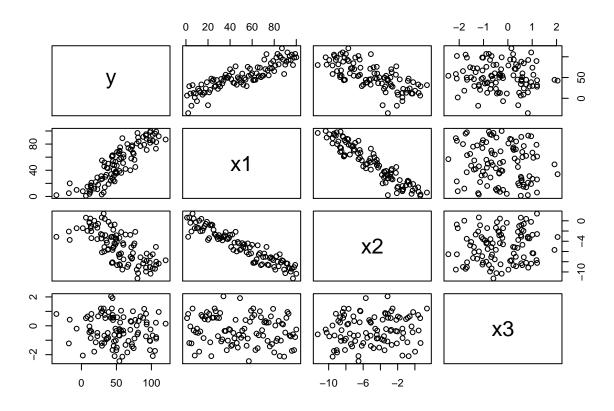
```
descriptives <- t( stat.desc(dat) )
write.table( descriptives, "clipboard", sep="\t", row.names=TRUE )</pre>
```

Scatterplots

pretty pairs plot

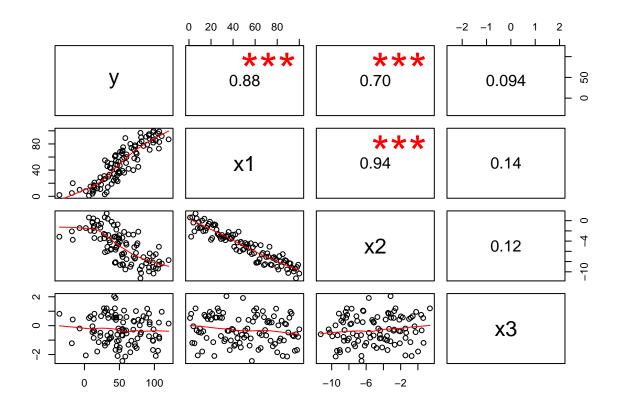
Convenient visual descriptives:

```
pairs( dat )
```



We can improve it:

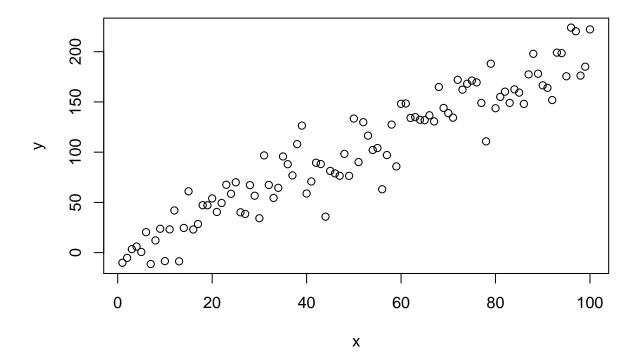
```
pairs( dat, lower.panel=panel.smooth, upper.panel=panel.cor)
```



Regression Syntax

create some data

```
x <- 1:100
y <- 2*x + rnorm(100,0,20)
plot(x, y)
```



```
dum <- sample( c("NJ","NY","MA","PA"), 100, replace=T )</pre>
```

$basic\ regression\ syntax$

The regression is run using the "linear model" command. The basic model will print the minimum output:

```
lm( y ~ x )

##
## Call:
## lm(formula = y ~ x)
##
## Coefficients:
```

```
## (Intercept) x
## -0.2333 2.0171
```

To generate nicely-formatted regression tables save the results from the regression as an object, and format the output for inclusion in a markdown document using the pander package.

```
m.01 <- lm( y ~ x )
summary( m.01 ) %>% pander # add pander to format for markdown docs
```

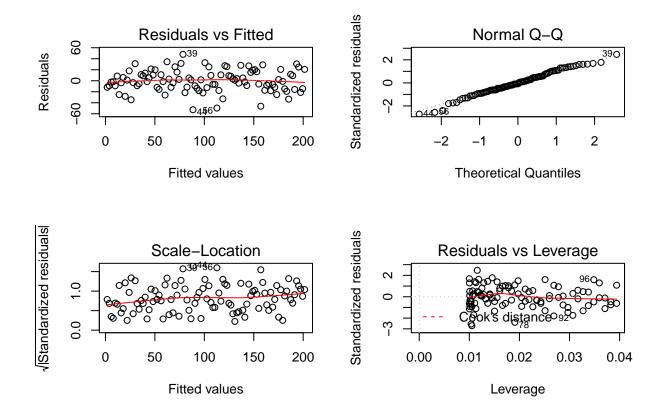
	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-0.2333	3.939	-0.05922	0.9529
x	2.017	0.06772	29.78	6.548 e-51

Table 7: Fitting linear model: y $\sim x$

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.55	0.9005	0.8995

nice visual diagnostics of model fit

```
par( mfrow=c(2,2) )
plot( m.01 )
```



useful model fit functions

```
coefficients( m.01 ) %>% pander # model coefficients
```

(Intercept)	X
-0.2333	2.017

confint(m.01, level=0.95) %>% pander # CIs for model parameters

	2.5 %	97.5 %
(Intercept)	-8.051	7.584
X	1.883	2.151

```
anova( m.01 )  # anova table
fitted( m.01 )  # predicted values
residuals( m.01 )  # residuals
influence( m.01 )  # regression diagnostics
library( coefplot )
```

Loading required package: ggplot2

```
m.02 \leftarrow lm(y \sim x1 + I(x1^2) + x2 + x3)
coefplot(m.02)
```



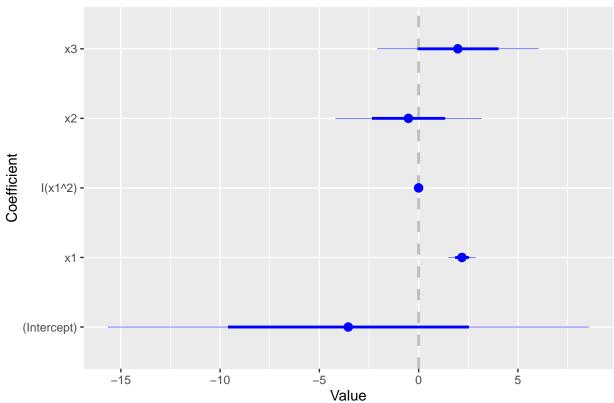


table with multiple regression models

	Model 1	Model 2	Model 3
(Intercept)	-0.233	-3.987	
	(3.939)	(5.993)	

	Model 1	Model 2	Model 3
x	2.017***	2.238***	2.014***
	(0.068)	(0.274)	(0.033)
x_sqr		-0.002	
		(0.003)	
R-squared	0.9	0.9	1.0
${f F}$	887.1	442.5	3626.4
p	0.0	0.0	0.0
${f N}$	100	100	100

specification

summary($lm(y \sim x1 + x2 + x3)) %>% pander$

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	0.0002184	3.976	5.493e-05	1
$\mathbf{x}1$	1.969	0.1991	9.886	2.611e-16
$\mathbf{x2}$	-0.5661	1.828	-0.3097	0.7574
x3	2.035	2.019	1.008	0.316

Table 12: Fitting linear model: $y \sim x1 + x2 + x3$

Observations	Residual Std. Error	R^2	Adjusted R^2
100	19.64	0.9017	0.8986

```
# add different functional forms
# square x1
summary( lm( y ~ x1 + x1^2 + x2 + x3 ) ) %>% pander # incorrect
```

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	0.0002184	3.976	5.493 e-05	1
x1	1.969	0.1991	9.886	2.611e-16
$\mathbf{x2}$	-0.5661	1.828	-0.3097	0.7574
x3	2.035	2.019	1.008	0.316

Table 14: Fitting linear model: $y \sim x1 + x1^2 + x2 + x3$

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.64	0.9017	0.8986

summary($lm(y \sim x1 + I(x1^2) + x2 + x3)$) %>% pander # correct - enclose with I()

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-3.544	6.054	-0.5855	0.5596
x1	2.181	0.3384	6.445	4.754e-09
$I(x1^2)$	-0.002056	0.002644	-0.7776	0.4387
$\mathbf{x2}$	-0.5157	1.833	-0.2814	0.779
x3	1.973	2.025	0.9746	0.3322

Table 16: Fitting linear model: $y \sim x1 + I(x1^2) + x2 + x3$

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.68	0.9023	0.8982

summary($lm(y \sim log(x1) + x2 + x3)$) %>% pander # log of x1 in formula works fine

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-49.12	12.34	-3.98	0.000134
$\log(x1)$	26.45	4.739	5.581	2.213e-07
$\mathbf{x2}$	-11.06	1.395	-7.931	3.983e-12
x3	1.077	2.488	0.4331	0.6659

Table 18: Fitting linear model: $y \sim \log(x1) + x2 + x3$

Observations	Residual Std. Error	R^2	Adjusted R^2
100	24.24	0.8502	0.8455

interactions

summary(lm(y ~ x1 + x2)) %>% pander

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.1118	3.974	-0.02813	0.9776
x1	1.955	0.1987	9.84	2.972e-16
$\mathbf{x2}$	-0.6045	1.828	-0.3308	0.7415

Table 20: Fitting linear model: $y \sim x1 + x2$

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.64	0.9006	0.8986

summary(lm(y ~ x1 + x2 + I(x1*x2))) %>% pander

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-0.1593	5.752	-0.0277	0.978

	Estimate	Std. Error	t value	Pr(> t)
x1	1.957	0.2437	8.031	2.448e-12
$\mathbf{x2}$	-0.6173	2.148	-0.2874	0.7744
I(x1 * x2)	0.0002887	0.02512	0.01149	0.9909

Table 22: Fitting linear model: $y \sim x1 + x2 + I(x1 * x2)$

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.74	0.9006	0.8975

summary(lm(y ~ x1*x2)) %>% pander # shortcut

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.1593	5.752	-0.0277	0.978
x1	1.957	0.2437	8.031	2.448e-12
$\mathbf{x2}$	-0.6173	2.148	-0.2874	0.7744
x1:x2	0.0002887	0.02512	0.01149	0.9909

Table 24: Fitting linear model: y ~ x1 * x2

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.74	0.9006	0.8975

dummy variables

summary(lm(y ~ x1 + x2 + x3 + dum)) %>% pander # drop one level

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	0.54	5.87	0.092	0.9269
$\mathbf{x}1$	1.991	0.2038	9.772	6.205 e-16
$\mathbf{x2}$	-0.2866	1.866	-0.1536	0.8782
x3	2.172	2.069	1.05	0.2965
$\operatorname{dum} \operatorname{NJ}$	-4.117	5.752	-0.7158	0.4759
$\operatorname{dum} \mathbf{N} \mathbf{Y}$	2.915	5.993	0.4863	0.6279
$\operatorname{dum}\operatorname{PA}$	0.6642	5.543	0.1198	0.9049

Table 26: Fitting linear model: y ~ x1 + x2 + x3 + dum

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.78	0.9033	0.8971

summary(lm(y ~ x1 + x2 + x3 + dum - 1)) %>% pander # keep all, drop intercept

	Estimate	Std. Error	t value	$\Pr(> t)$
x1	1.991	0.2038	9.772	6.205 e-16
x2	-0.2866	1.866	-0.1536	0.8782
x3	2.172	2.069	1.05	0.2965
\mathbf{dumMA}	0.54	5.87	0.092	0.9269
$\operatorname{dum} NJ$	-3.577	4.942	-0.7239	0.4709
$\operatorname{dum} \mathbf{N} \mathbf{Y}$	3.455	5.21	0.663	0.509
dumPA	1.204	5.591	0.2154	0.8299

Table 28: Fitting linear model: y ~ x1 + x2 + x3 + dum - 1

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.78	0.9742	0.9722

Standardized Coefficients and Robust Standard Errors

standardized regression coefficients (beta)

```
library( lm.beta )
m.01.beta <- lm.beta( m.01 )
summary( m.01.beta ) # %>% pander
##
## Call:
## lm(formula = y \sim x)
## Residuals:
      Min
               1Q Median
                               3Q
                                      Max
## -52.697 -11.984 -1.411 12.248 48.008
##
## Coefficients:
##
              Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept) -0.23329
                            0.00000
                                       3.93926 -0.059
                                                          0.953
## x
               2.01710
                            0.94896
                                       0.06772 29.785
                                                         <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 19.55 on 98 degrees of freedom
## Multiple R-squared: 0.9005, Adjusted R-squared: 0.8995
## F-statistic: 887.1 on 1 and 98 DF, p-value: < 2.2e-16
# coef( m.01.beta )
```

```
# note the standard error is not standardized - describes regular coefficients
summary( m.01 ) %>% pander
```

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-0.2333	3.939	-0.05922	0.9529
x	2.017	0.06772	29.78	6.548 e-51

Table 30: Fitting linear model: $y \sim x$

Observations	Residual Std. Error	R^2	Adjusted \mathbb{R}^2
100	19.55	0.9005	0.8995

or just use the formula:

```
lm.beta <- function( my.mod )
{
    b <- summary(my.mod)$coef[-1, 1]
    sx <- sd( my.mod$model[,-1] )
    sy <- sd( my.mod$model[,1] )
    beta <- b * sx/sy
    return(beta)
}

coefficients( m.01 ) %>% pander
```

(Intercept)	х
-0.2333	2.017

```
lm.beta(m.01) \%>\% pander
```

0.949

robust standard errors

```
# install.packages( "sandwhich" )
# install.packages( "lmtest" )

library(sandwich)
library(lmtest)

m.01 <- lm( y ~ x )

# REGULAR STANDARD ERRORS - not robust

summary( m.01 ) %>% pander
```

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-0.2333	3.939	-0.05922	0.9529
x	2.017	0.06772	29.78	6.548 e-51

Table 33: Fitting linear model: y $\sim x$

Observations	Residual Std. Error	R^2	Adjusted R^2
100	19.55	0.9005	0.8995

```
# ROBUST STANDARD ERRORS
# reproduce the Stata default
coeftest( m.01, vcov=vcovHC(m.01,"HC1") ) # robust; HC1 (Stata default)
##
## t test of coefficients:
##
            Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.233294 3.469377 -0.0672 0.9465
## x
            ## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# ROBUST STANDARD ERRORS
# check that "sandwich" returns HCO
                                     # robust; sandwich
coeftest(m.01, vcov = sandwich)
##
## t test of coefficients:
##
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.233294 3.434508 -0.0679 0.946
## x
            ## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
coeftest(m.01, vcov = vcovHC(m.01, "HCO")) # robust; HCO
##
## t test of coefficients:
##
            Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.233294 3.434508 -0.0679 0.946
## v
            ## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# ROBUST STANDARD ERRORS
\# check that the default robust var-cov matrix is HC3
coeftest(m.01, vcov = vcovHC(m.01)) # robust; HC3
## t test of coefficients:
##
            Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.233294 3.517347 -0.0663 0.9473
## x
```