Big Data Analytics Academic Year 2023-2024

Simone Borra

Informations

Week	day	hours	Teaching	
week1	March 6	14:00-16:00	Prof Borra	Introduction
week1	March 7	14:00-16:00	Prof Borra	Introduction
week2	March 22	14:00-17:00	SAS – (Zoom)	SAS Visual Analytics
week2	day1	4 hours	SAS e-learn	SAS Visual Analytics
week3	April 5	14:00-17:00	SAS – (Zoom)	SAS Visual Analytics
week3	day1	4 hours	SAS e-learn	SAS Visual Analytics
week4	April 12	14:00-17:00	SAS – (Zoom)	SAS Visual Analytics
week4	day1	4 hours	SAS e-learn	SAS Visual Analytics
week4	day2	3 hours	SAS e-learn	SAS Visual Analytics
week8	19 April	9:00-12:00 14:00-17:00	SAS – (Zoom)	SAS Case Study
week8	?	9:00-11:00	Prof Borra	Conclusions
Final Exam	?	3 hours	Prof Borra (exam)	

Exam

The final exam consists of two parts:

Part 1 (Theory): Multiple choice test concerning the theoretical aspects
1 hour
Part 2 (Practice): Questions about using SAS Visual Analytics on real data
1 hour

Aims

The course provides an introduction to data preparation, data analysis and report creation in **SAS Visual Analytics**.

Students will learn how to use this point-and-click SAS environment to:

- **access, transform** and **modify data**
- **visually explore data to discover new insights**.

This Data Visualization tool by SAS enable to easily search for:

- **Relationships**
- **Trends**
- **patterns**

Teaching Method

Classroom teaching: a SAS expert will describe the main topics of the course and will answer students' questions.

E-learning: a collection of **videos**, **demos**, and practices, that summarize the concepts shown in classroom.

Case studies: in which students can practice with the supervision of the teacher.

The final exam consists of a written test containing open-ended and/or closed-ended questions, covering all the topics of the course.

Certification

Lectures and e-learning lessons can help students prepare for the certification exam:

SAS Certified Specialist: Visual Business Analyst.

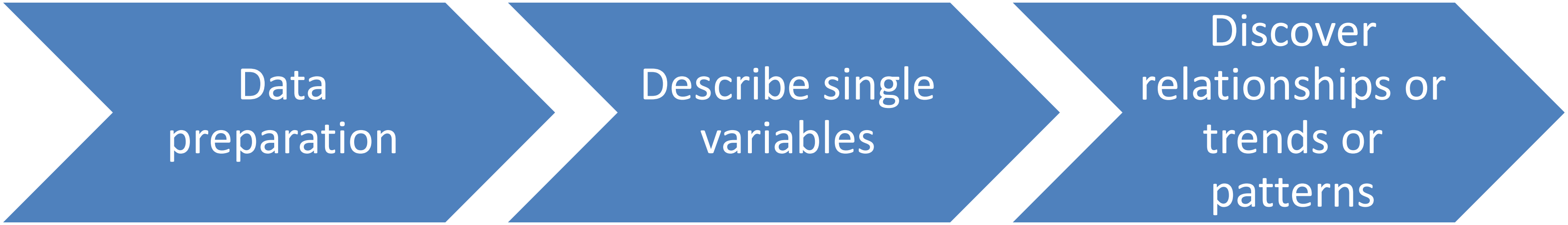
To complete the preparation, the student will have to dedicate time to carry out the e_learning module:

SAS Visual Analytics 2 for SAS Viya: Advanced

All certification details are described in:
https://www.sas.com/sas/training/scyp.html.

Roadmap

Roadmap to analyse Big Data



Data preparation

Describe single variables

Discover relationships or trends or patterns

Data preparation

Sample data could be collected in several ways:

1. variables are measured on *n* different units, in a certain istant
2. variables are measured in *T* different times
3. variables are measured in *T* different times always on the same *n* units

consequently we have the following approaches:

1. Cross section analysis
2. Analysis for time series
3. Analysis for panel data

Data preparation

	t=1	
ID	X_1	X_2
12	x_{11}	x_{12}
34	x_{21}	x_{22}
...	...	....
25	x_{n1}	x_{n2}

	t=2	
ID	X_1	X_2
33	x_{11}	x_{12}
72	x_{21}	x_{22}
...	...	....
86	x_{n1}	x_{n2}

	t=3	
ID	X_1	X_2
43	x_{11}	x_{12}
101	x_{21}	x_{22}
...	...	....
122	x_{n1}	x_{n2}

	t=4	
ID	X_1	X_2
6	x_{11}	x_{12}
210	x_{21}	x_{22}
...	...	....
66	x_{n1}	x_{n2}

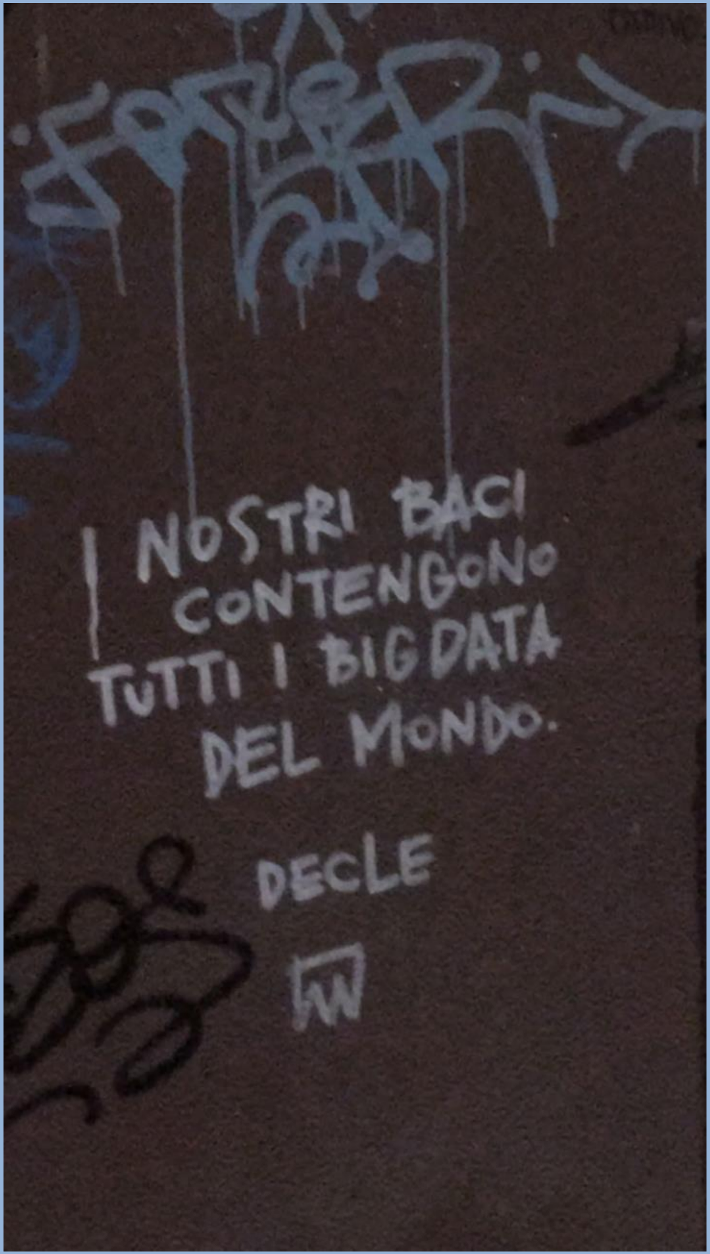
	t=1	
ID	X_1	X_2
12	x_{11}	x_{12}
34	x_{21}	x_{22}
...	...	....
25	x_{n1}	x_{n2}

	t=2	
ID	X_1	X_2
12	x_{11}	x_{12}
34	x_{21}	x_{22}
...	...	....
25	x_{n1}	x_{n2}

	t=3	
ID	X_1	X_2
12	x_{11}	x_{12}
34	x_{21}	x_{22}
...	...	....
25	x_{n1}	x_{n2}

	t=4	
ID	X_1	X_2
12	x_{11}	x_{12}
34	x_{21}	x_{22}
...	...	....
25	x_{n1}	x_{n2}

Our kisses contain all the big data in the world



Big Data - three Vs definition: **V**olume **V**elocity **V**ariety

Sources of Big Data (UNECE, 2013)

1. Social Networks (human-sourced information)

Social networks (Facebook, Twitter,…), Blogs, Pictures (Instagram, Picasa,…) Video (Youtube,…), Internet searchers, Mobile data content (Whatsapp,…), Email,…, ecc.

2. Traditional Buiness systems (process-mediated data)

Data produced by Public Agencies, Data produced by businesses: commercial transactions, Banking/stock records, Credit cards, E-commerce,…ecc.

3. Internet of Things (machine-generated data)

Data from fixed sensors:

Home automation; Weather/pollution sensors; Traffic sensors/webcam; Security/surveillance videos/images; Scientific sensors

Data from Mobile sensors (tracking):

Mobile phone location; Cars; Satellite images

Data from computer systems:

Logs; Web logs; ecc

Big Data - Advantages

- With a big number of cases should be able to discover and estimate more complex relationship between variables.
- If we do not have a small sample but a very large number of observations chosen randomly, it is of little relevance to consider the **sampling variability of the estimators** of the population parameters.
- In fact, the sample variability tends to decrease as the sample size increases and we can assume that a very large unbiased sample represents the phenomena and their relationships as occurs in the population.

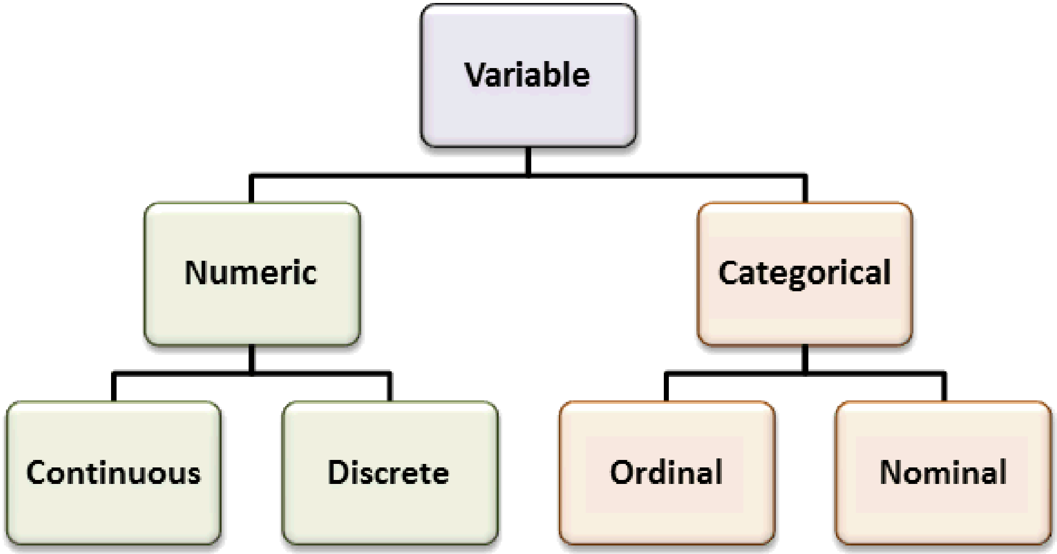
In general, a large amount of data is not a sufficient condition for obtaining good statistical analyzes

Big Data - Disadvantages

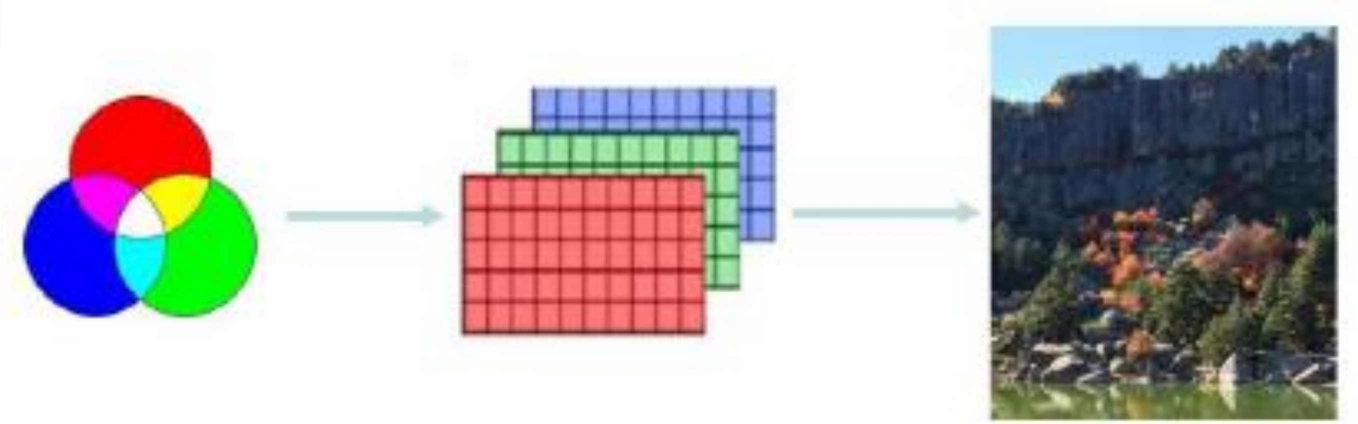
- Big data **often cannot be considered as a random sample** and this could strongly distort the analysis;
- Data are often observed and recorded without taking into account subsequent statistical analyzes, and it is quite common that **some essential variables are missing**.
- Data often comes from different sources and always requires cleaning work that considers missing data and inconsistencies.
- As the number of variables increases the possibility of **spurious associations between variables**.

Data type

For the first time in history we have data everywhere, the now called **Big Data**. These data are a mixture of **structured** and **unstructured** information.
P.Galeano-D. Pena (2019)
Large heterogeneous databases sometimes **unstructured**, which may include **texts**, **images**, **videos**, or **sounds**, from different populations and as many (or even more) variables than observations.
We will only consider **structured data**:



Example: Process of transforming pixels in images



For example, a grid 10X10 = 100 cells
In each cell we have three numbers:
Intensity of red; intensity od green; intensity of Blue
We have 100X3=300 numbers to transform a set of pixels into a image

Data type

Data type

Depending on the type of variable we can use different statistical tools to reclassify, transform and analyze variables.

Data preparation

Using several sources of data we need to homogenize data and integrate different tables of data.

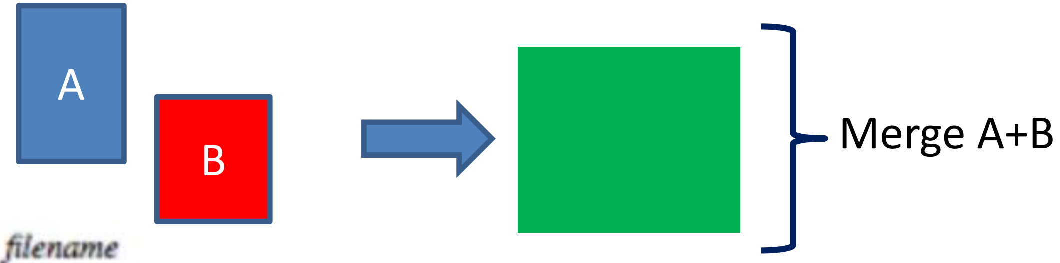
Data preparation

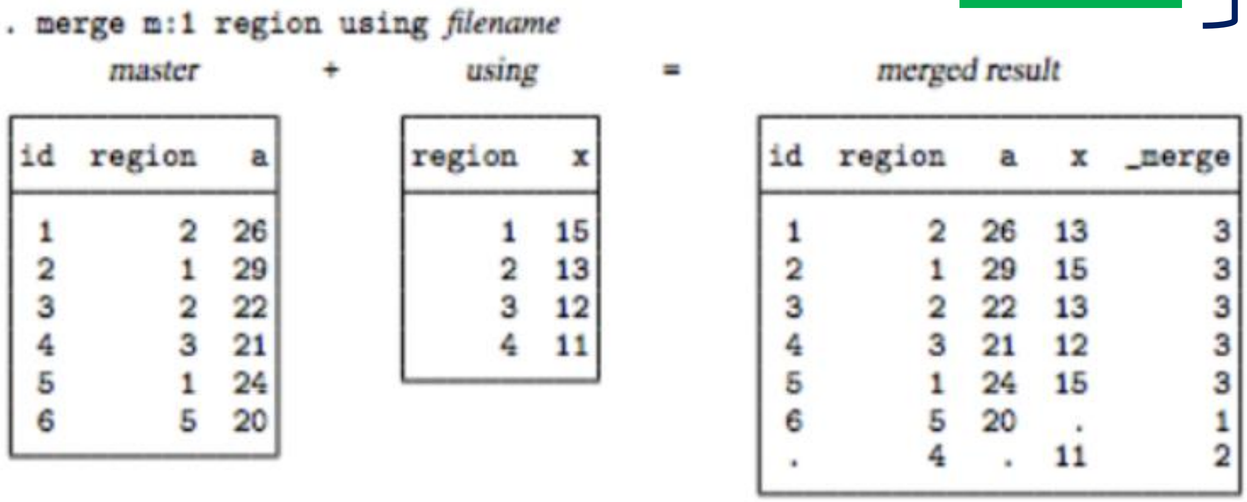
Using several sources of data we need to homogenize data and integrate different tables of data.

Merge

Merge adds columns, or variables. You would use merge when there are the same observations across datasets with different variables.

Many-to-one-merge





```
. merge m:1 region using filename
```

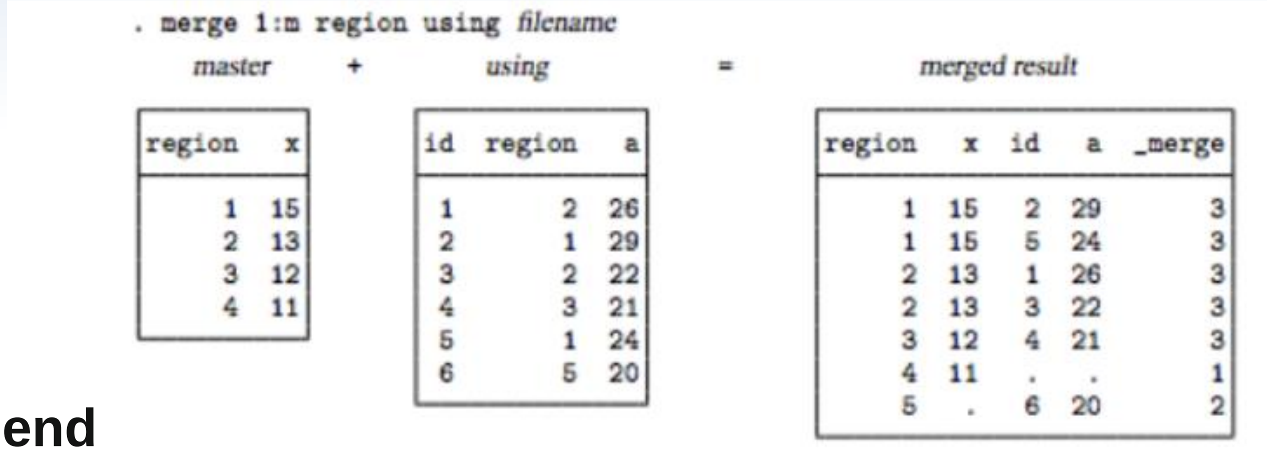
master + *using* = *merged result*

id	region	a
1	2	26
2	1	29
3	2	22
4	3	21
5	1	24
6	5	20

region	x
1	15
2	13
3	12
4	11

id	region	a	x	_merge
1	2	26	13	3
2	1	29	15	3
3	2	22	13	3
4	3	21	12	3
5	1	24	15	3
6	5	20	.	1
.	4	.	11	2

One-to-Many-merge



```
. merge 1:m region using filename
```

master + *using* = *merged result*

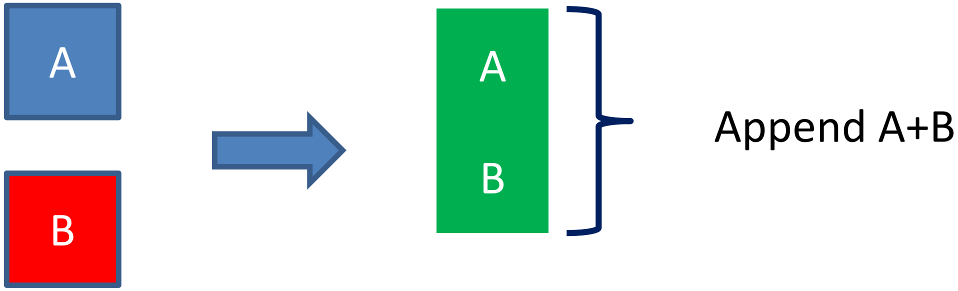
region	x
1	15
2	13
3	12
4	11

id	region	a
1	2	26
2	1	29
3	2	22
4	3	21
5	1	24
6	5	20

region	x	id	a	_merge
1	15	2	29	3
1	15	5	24	3
2	13	1	26	3
2	13	3	22	3
3	12	4	21	3
4	11	.	.	1
5	.	6	20	2

Append

Is used when you want combine datasets that contain the same variables, but have different cases, thus, you are adding rows to the dataset, but the number of columns should remain the same.



Append A+B

Data integration

Set of Techniques for joining different tables and ensuring data consistency: mesurement units, type of variable …

customer	Age	Educ level
Paolo	23	Secondary school dipl
Francesca	45	Degree
Erik	41	Secondary school dipl
Maria	29	Primary school dipl

Data-set A

customer	Age	Educ level
Erik	41	Medium
John	27	High
Maria		Low
Alan	41	Low

Data-set B

customer	Age	Educ level
Erik	41	Medium
John	27	High
Maria	29	Low
Paolo	23	Medium
Francesca	45	High
Alan	41	Low

Data-set A+B

Educational level “Primary school dipl.” = “Low”

Educational level “Secondary school dipl.” = “Medium”

Educational level “Degree” = “High”

Data trasformation and reclassification

Transformation of **nominal** variables into **quantitative** variables

We use dummy variables, with only two values: 1 or 0.

Example: Gender Male=0 Female=1

If the variables has K modalities we use K-1 dummy variables.

For instance, K=3 we use 2 dummy:

Name	Employment status	Dummy1	Dummy2
Jack	Full-time employed	1	0
Anna	Part-time employed	0	1
Mark	Unemployed	0	0

Transformation of **ordinal** variables into **quantitative** variables

For each modality we use an interger value

Example:

Educational level

Elementary=1 Middle=2 High=3 Degree=4 Post-Degree=5

Degree of satisfaction

Very dissatisfied=-2
Dissatisfied =-1
Neutral=0
Satisfied=+1
Very satisfied=+2

The reclassification is a very discretionary that could greatly influence subsequent analysis

Subdivision of the quantitative variable into classes

In many situations it is convenient to divide the quantitative character into different classes of values

Example:
In a Labour forces context these classes could be used

Age in 3 classes :

from 0 to 16; from 16 to 65; greater than 65 up to 110.
student employed retired

- The number of classes must be adequate to the problem
- Classes must not overlap
- Classes must include all possible values

Data preparation

For many statistical analysis it is convenient to first treat the characters in order to make them homogeneous with each other.
In particular, two quantitative characters can differ for:

- measurement unit (weight in Kg, height in cm)
- different intensity (average weight between adults is 70 Kg, average weight between newborns is 3,5 Kg)
- different variability (the income could vary between 500 and 3000 euro, or between 500 and 10.000 euro)

In order to homogenize the observed characters, **normalization** and **standardization** techniques can be applied to them.

How to transform the values of a feature in such a way that all the transformed values are within a certain range.

For instance, we observe the following values for X:

2; 3; 4; 12; 23; 32; 34; 67

The minimum and maximum values are min=2 e max=67.

We want to transform the values so that the new feature X‘ has min_new = 1 and max_new = 10.

We apply on the original values this function:

$$X' = \frac{X - min}{max - min} \times (max\_new - min\_new) + min\_new$$

If X=2 we obtain:

$$X' = \frac{2-2}{67-2} \times (10-1) + 1 = 0 + 1 = 1$$

If X=67 we obtain:

$$X' = \frac{67-2}{67-2} \times (10-1) + 1 = 9 + 1 = 10$$

The values of X’ are:

1; 1,39; 2,38; 3,91; 5,15; 5,43; 6,82 ; 10

How to transform the values of a feature so that the mean will be 0.

For instance, we observe the following values for X:

2; 3; 12; 23; 32; 34; 44; 67

The mean is (12+3+32+67+23+44+2+34)/8=27,125

To transform the values of a feature so that the mean will be 0, we apply:

$$X' = X - mean(X)$$

Obtaining:

-25,125; -24,125; -15,185; -4,125; 4,875; 6,875; 16,875; 39,875

and now the average value is equal to 0.

STANDARDIZATION: How to transform the values of a feature so that the mean will be 0 and variance 1.

For instance, we observe the following values for X:

2; 3; 12; 23; 32; 34; 44; 67

The mean is (2+3+12+23+32+34+44+67)/8=27.125

The variance is [(2-27.125)^2+…+(67-27.125)^2]/8=425.6

The standard deviation =$\sqrt{425.6} = 20.6$

To transform the values of a feature so that the mean will be 0 variance 1, we apply:

$$X' = \frac{X - mean(X)}{stand.dev.(X)}$$

Obtaining:

-1.218; -1.169; -0.733; -0.200; 0.236; 0.333; 0.818; 1.933

and now the average value is equal to 0 and the variance is 1.

Data preparation

The data may contain **missing values**, i.e. for some statistical units only a part of the variables of interest may have been detected.

For instance, Bianchi's age is missing, the Dotti's is missing.

Name	Age	Sex	Educ lev	Activity	Weight (kg)	Exam Score
Rossi M.	32	M	degree	employed	72	65
Bianchi G.	🟥	F	degree	employed	55	55
Nicoletti C.	46	M	diploma	unemployed	79	53
Marcelli F.	28	M	diploma	student	63	78
Petrone A.	51	F	diploma	housewife	64	21
Dotti P.	33	M	degree	🟥	64	66

Data preparation

There are several techniques of dealing with missing data.
The simplest, but also the most expensive in terms of information loss, is to eliminate cases corresponding to the missing values.

Name	Age	Sex	Educ lev	Activity	Weight (kg)	Exam Score
Rossi M.	32	M	degree	employed	72	65
~~Bianchi G.~~	🟥	~~F~~	~~degree~~	~~employed~~	~~55~~	~~55~~
Nicoletti C.	46	M	diploma	unemployed	79	53
Marcelli F.	28	M	diploma	student	63	78
Petrone A.	51	F	diploma	housewife	64	21
~~Dotti P.~~	~~33~~	~~M~~	~~degree~~	🟥	~~64~~	~~66~~

this method leads to a reduction in the sample size. Consequences: **biased estimates, reduced reliability of estimates**.

Data preparation

If the variable is **quantitative**, another method is to replace the missing value with the average (median) of the observed values on the remaining statistical units.

For instance, The mean value of Age is:

(32+46+28+51+33)/5=38

Name	Age	Sex	Educ lev	Activity	Weight (kg)	Exam Score
Rossi M.	32	M	degree	employed	72	65
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Marcelli F.	28	M	diploma	student	63	78
Petrone A.	51	F	diploma	housewife	64	21
Dotti P.	33	M	degree	🟥	64	66

Consequence: this method **reduce the feature variability**

Another method is to replace the missing value with that observed statistical unit most similar to that considered. There are many ways to define the "similarity" between two statistical units.

Dotti P. presents values with respect to age, sex, educational qualification and score very “close” to those presented by Rossi. Therefore, Dotti's activity is attributed to Rossi, that is “employed”.

Name	Age	Sex	Educ lev	Activity	Weight (kg)	Exam Score
Rossi M.	32	M	degree	employed	72	65
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Petrone A.	51	F	diploma	housewife	64	21
Dotti P.	33	M	degree	employed	64	66

donor imputation is to fill in the missing values for a given unit by copying observed values of another unit, the donor.

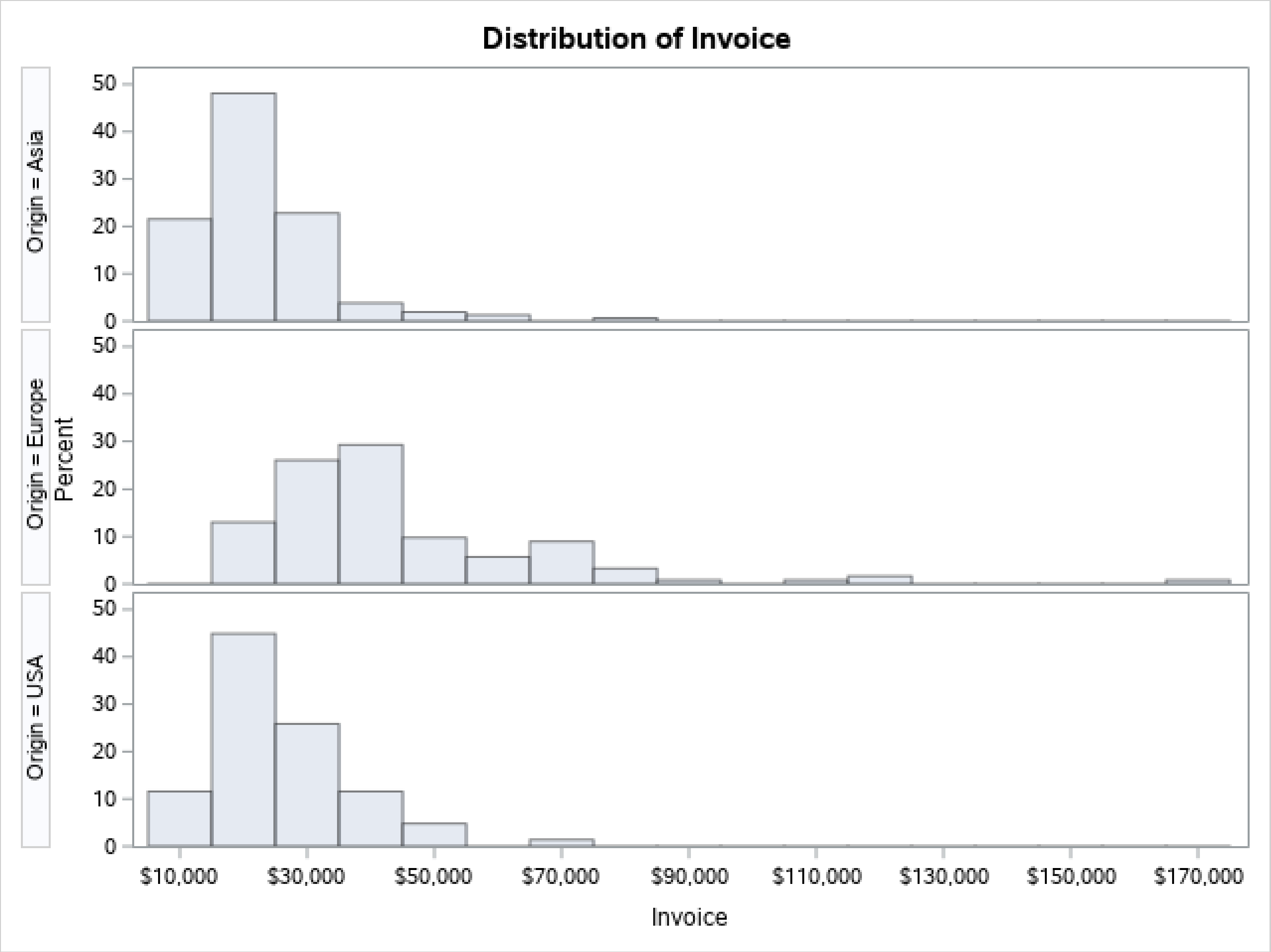
Feature description

Description of a single feature

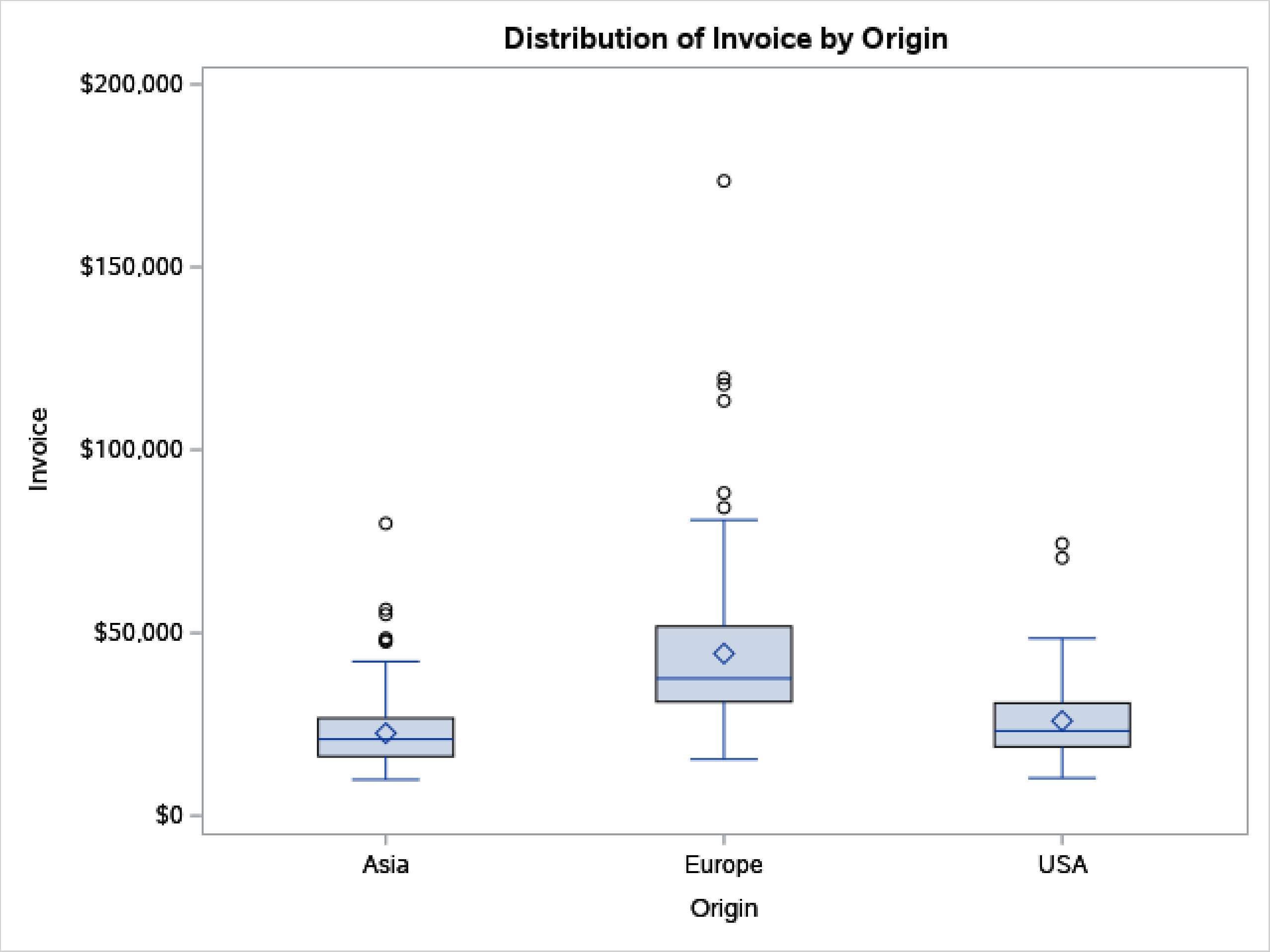
For a categorical/quantitative variable

- Frequency distribution
- Position Indices
- Dispersion Indices
- % of missing data
- Presence of outliers or extreme values

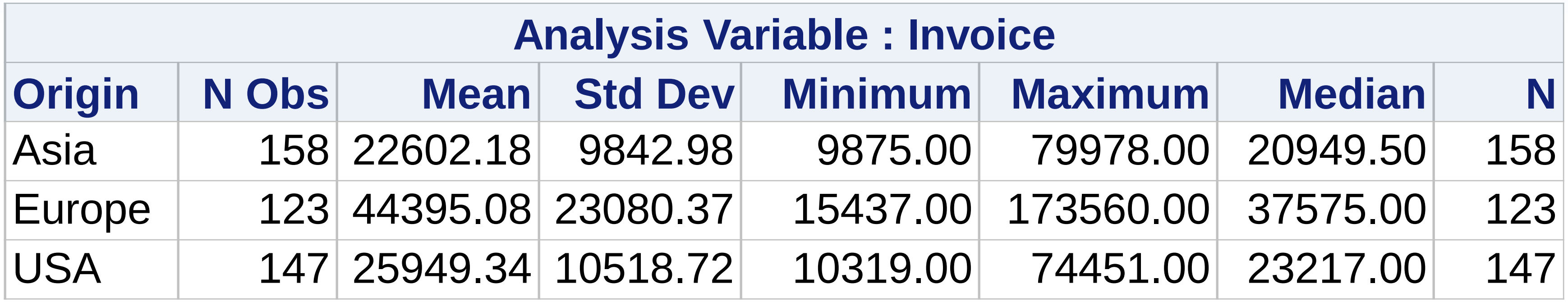
Feature description



Feature description



Feature description



Analysis Variable : Invoice							
Origin	**N Obs**	**Mean**	**Std Dev**	**Minimum**	**Maximum**	**Median**	**N**
Asia	158	22602.18	9842.98	9875.00	79978.00	20949.50	158
Europe	123	44395.08	23080.37	15437.00	173560.00	37575.00	123
USA	147	25949.34	10518.72	10319.00	74451.00	23217.00	147

Association

Several indices in order to measure association between two variables:

- Nominal vs Nominal: Chi-square (0 ; +∞) , V-Cramer (0 ; 1)
- Ordinal vs Ordinal: Gamma (-1 ; +1), Tau-b Kendal (-1 ; +1)
- Quantitative vs Quantitative: Correlation index (-1 ; +1)

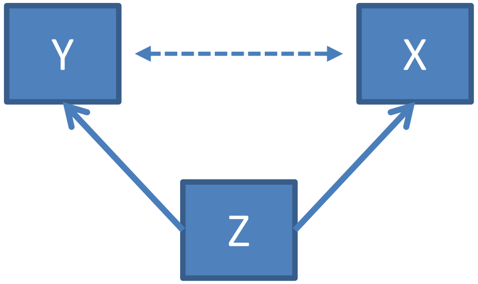
Association

Were you satisfied with your experience today?
1=very Unsatisfied, 2, 3, 4, 5= very Satisfied

Did our product/service meet your expectations?
1=absolutely No, 2, 3, 4, 5= absolutely Yes

Spurious correlation

In simple linear regression frequently we have spurious correlation, when two variables Y and X have no direct causal connection, yet it may be wrongly inferred that they do, due to either coincidence or the presence of a certain third, unseen factor Z.

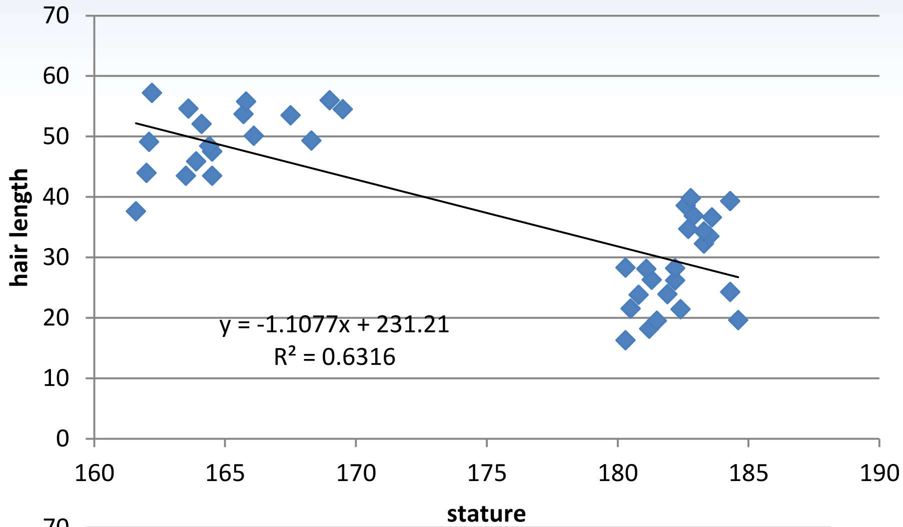


For instance we consider a sample student

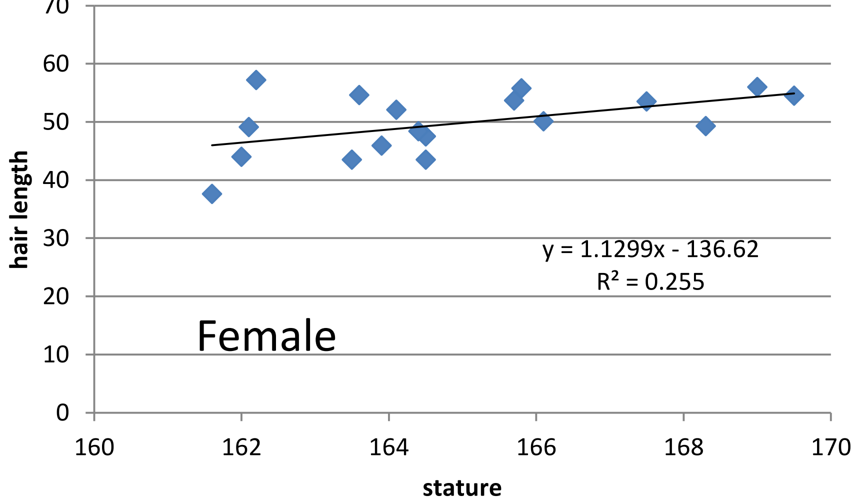
We observe Stature and Hair length

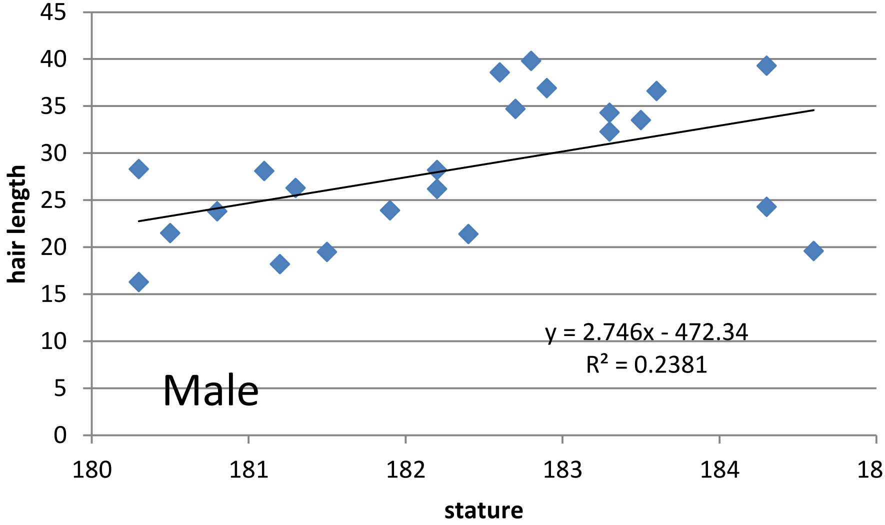
We estimate simple linear regression with Y= Hair length and X=Stature

Spurious correlation



but considering the **sex** we obtain





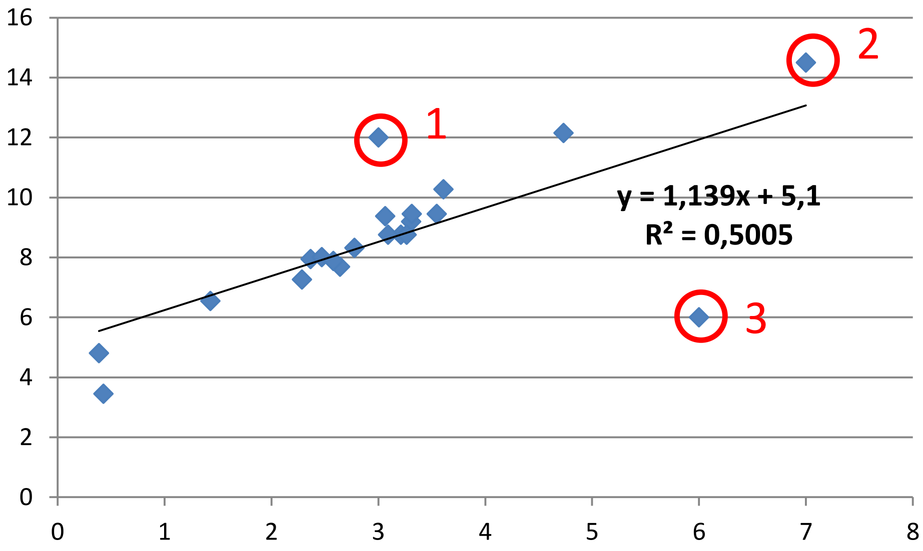
Presence of outliers

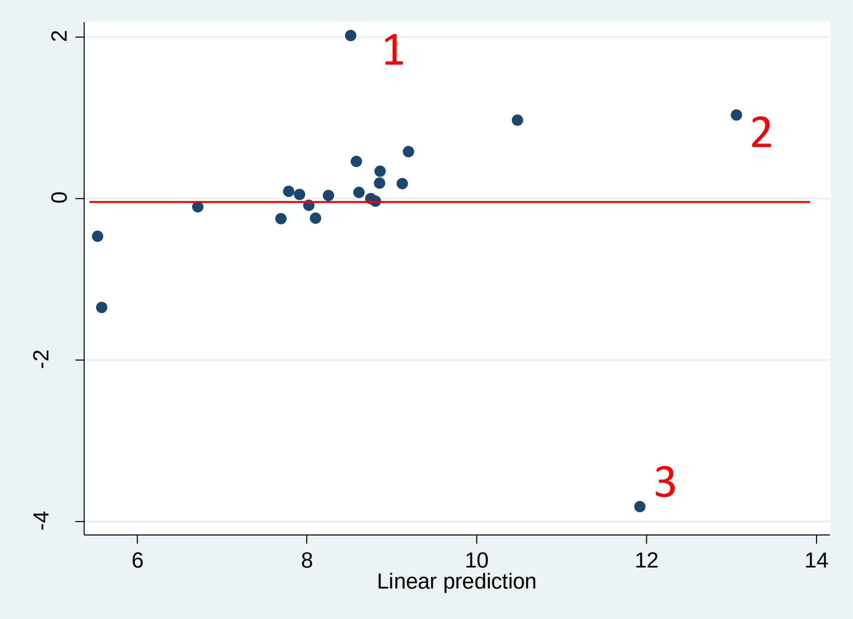
Three different types of outliers:

1: a value of Y very different from the whole sample but not X

2: values of X and Y very different from the whole sample

3: a value of X very different from the whole sample but not Y





Presence of outliers

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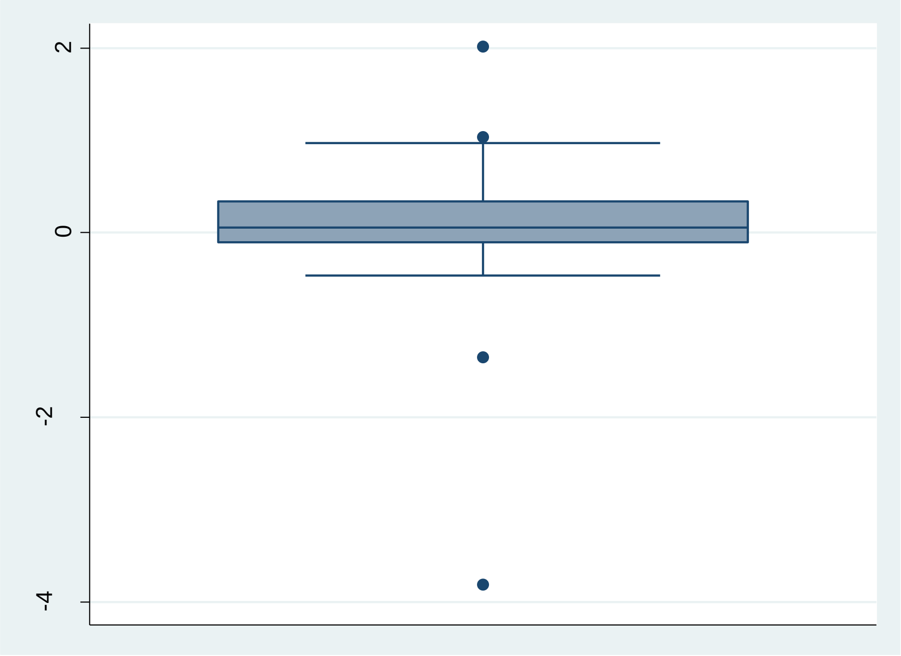
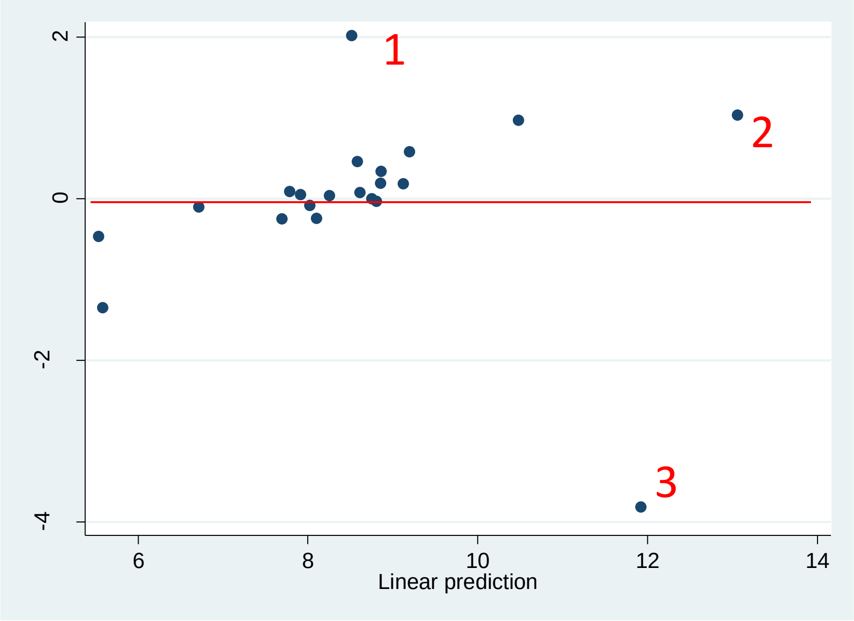
3: a value of X very different from the whole sample but not Y





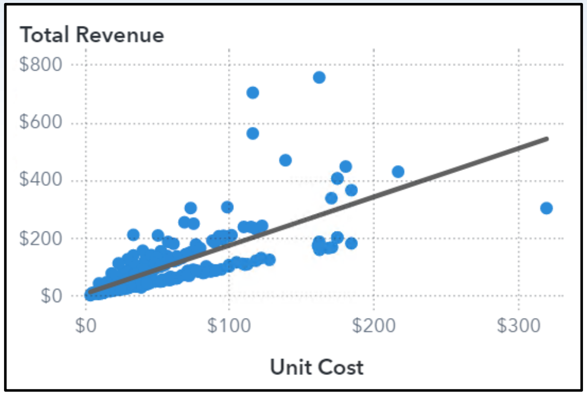
Fit Line

Fit lines can be added to scatter plots and heat maps to plot the relationship between variables. The following types of fit lines are available:

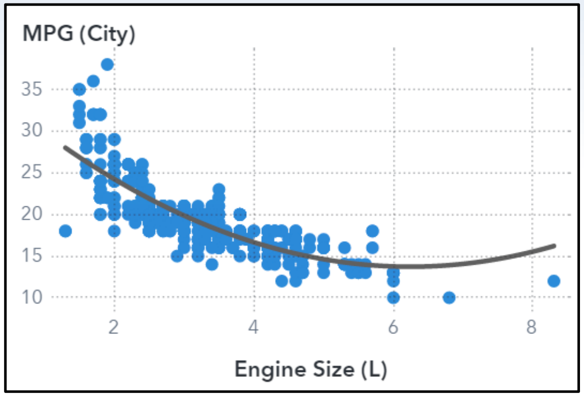
Linear – creates a linear fit line (a straight line that best represents the relationship between measures) using a linear regression algorithm.
Quadratic – creates a quadratic fit line (a line with a single curve that best represents the relationship between measures).
Cubic – creates a cubic fit line (a line with two curves that best represents the relationship between measures). This method often produces a line with an S shape.
PSpline – creates a penalized B-spline, which is a smoothing spline that closely fits the data. This method can display a complex line with many changes in its curvature.

Fit Line

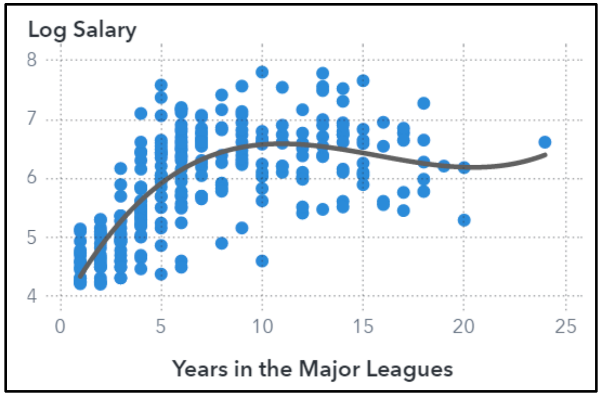
Linear



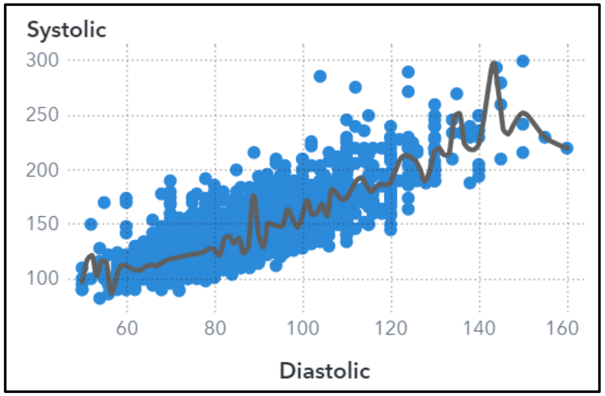
Quadratic



Cubic



PSpline



Fit Line

Running mean smoother

$$s(x_i) = \underset{j \in I_K(x_i)}{ave} (y_j)$$

Running line smoother

Average

we compute a least-squares line instead of a mean in each neighbourhood.

$$s(x) = \hat{\alpha} + \hat{\beta}x \quad x \in I_K(x_i)$$

where $\hat{\alpha}$ and $\hat{\beta}$ are LS estimates for the data points in $I_k(x_i)$.

Locally weighted running line smoother

Average

For each point in $I_k(x_0)$ we give a weight w_i calculated by means of **Tri-cube** function:

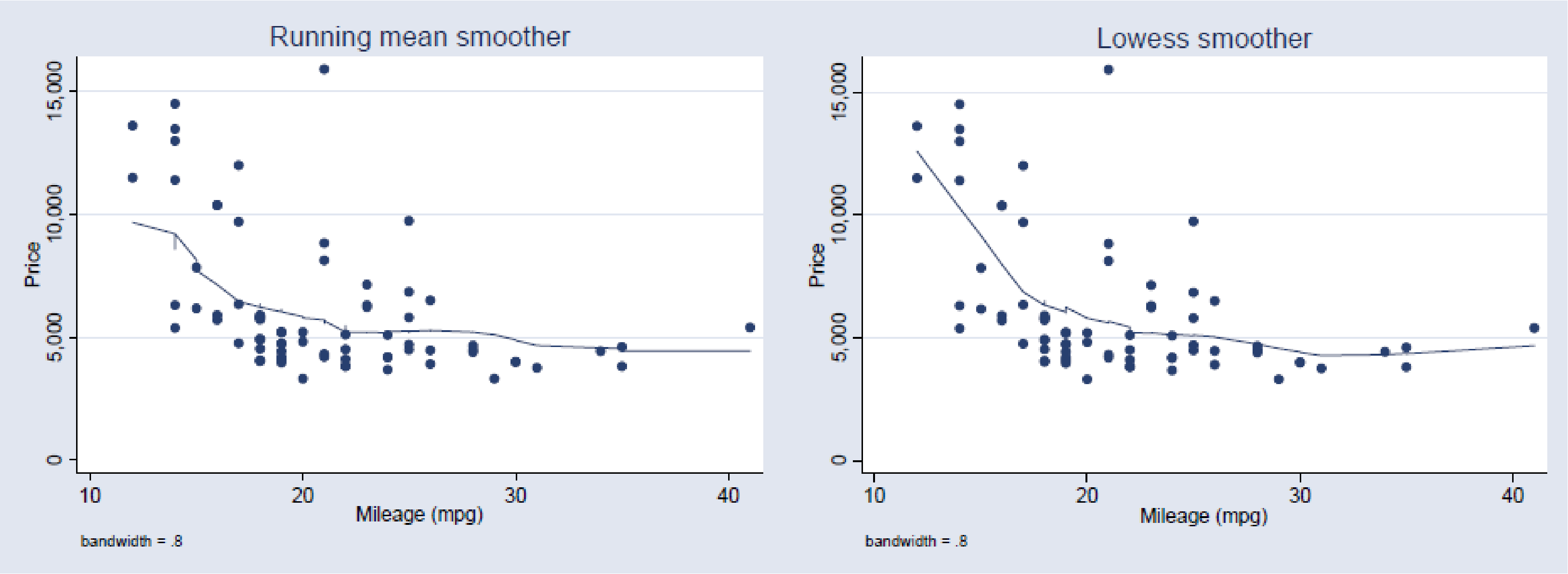
$$W\left(\frac{|x_0 - x_i|}{d_K}\right) \qquad W(u) = \begin{cases} \left(1 - |u|^3\right)^3 & |u| \leq 1 \\ 0 & otherwise \end{cases}$$

we compute a weighted least-squares line in each neighbourhood.

$$s(x_0) = \hat{\alpha}(x_0) + \hat{\beta}(x_0)x_0$$

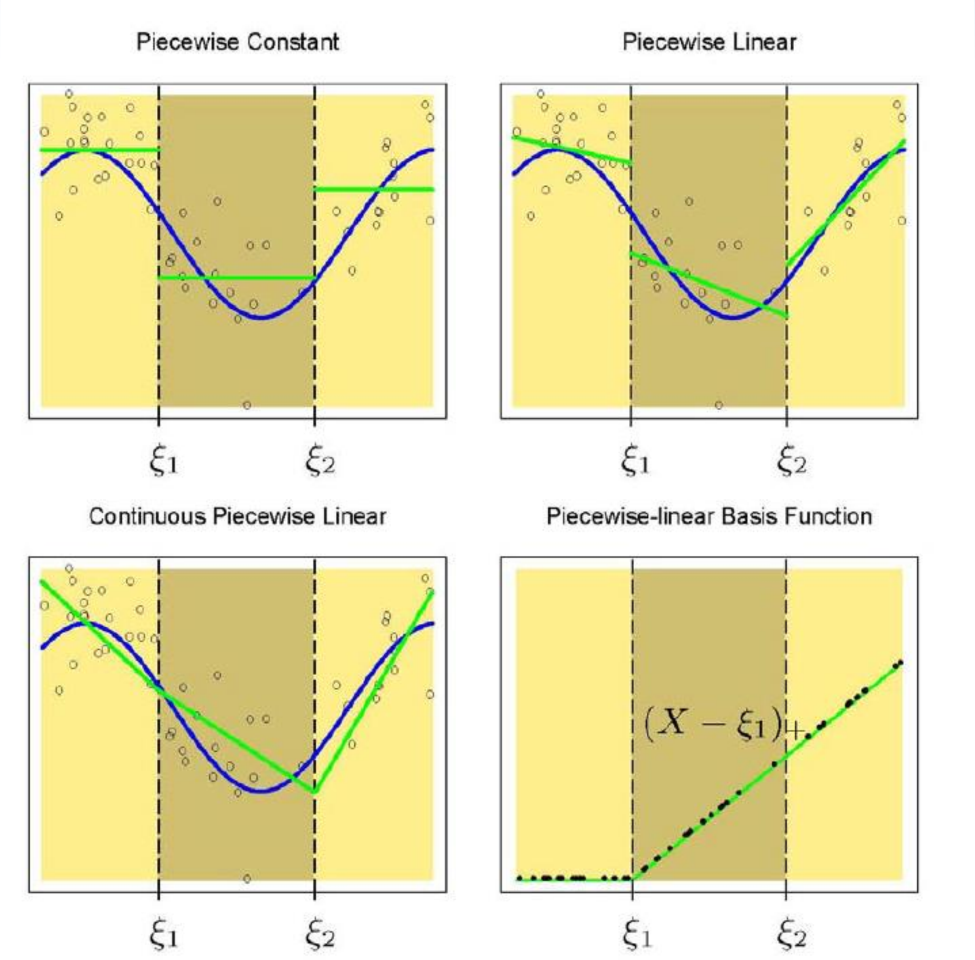
Fit Line

Bandwith=0.8

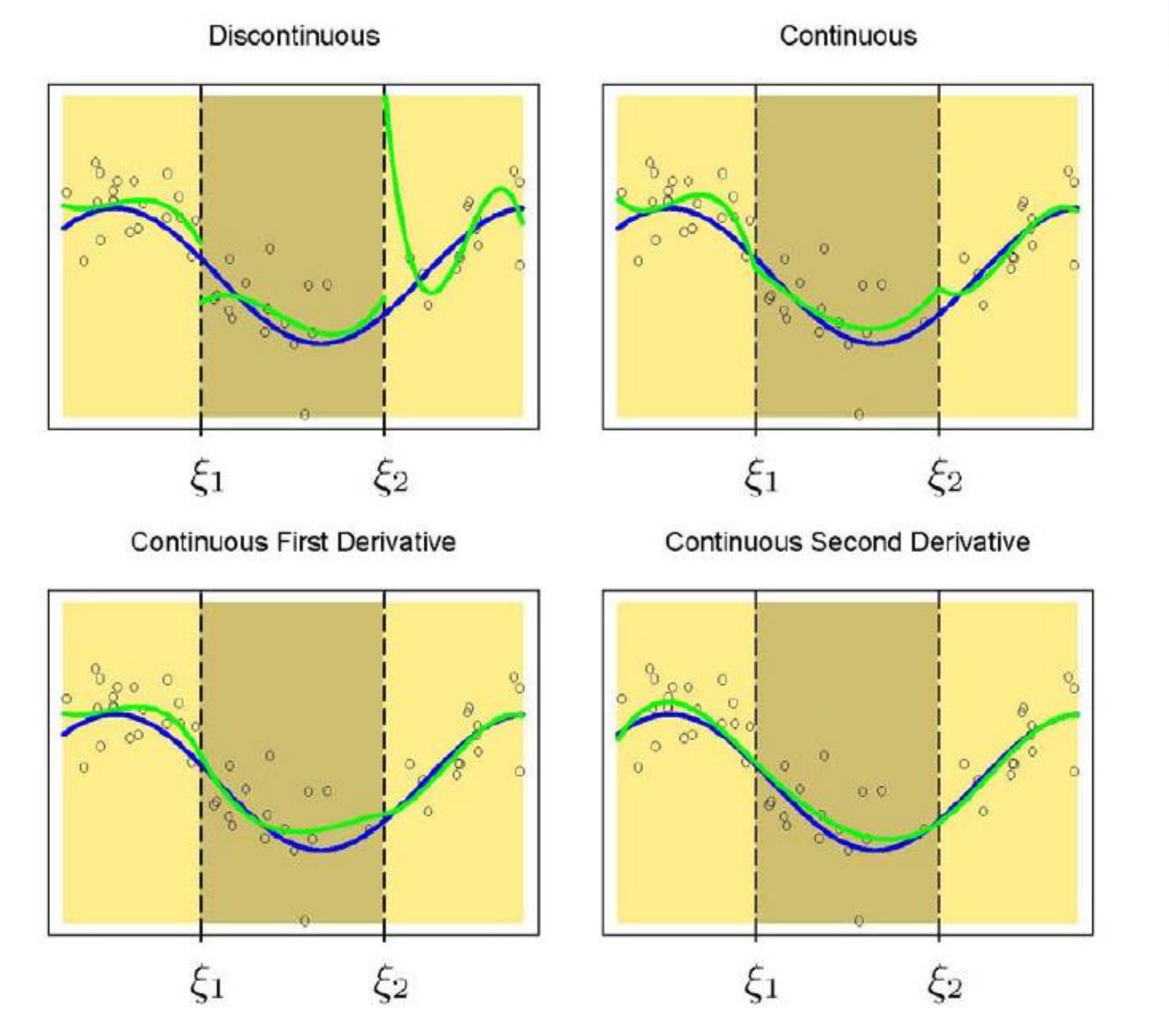


Fit Line

Spline - linear

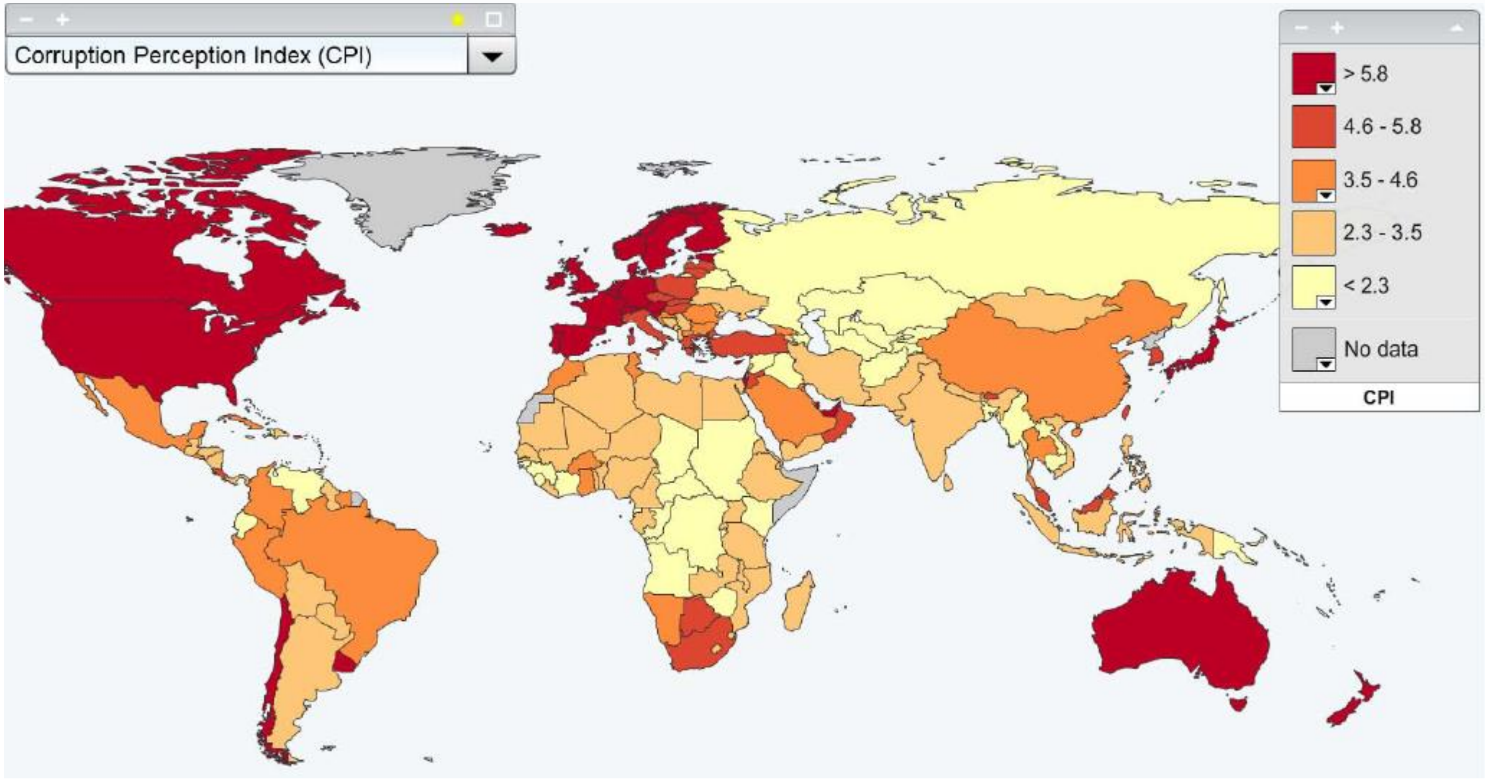


Spline - cubic



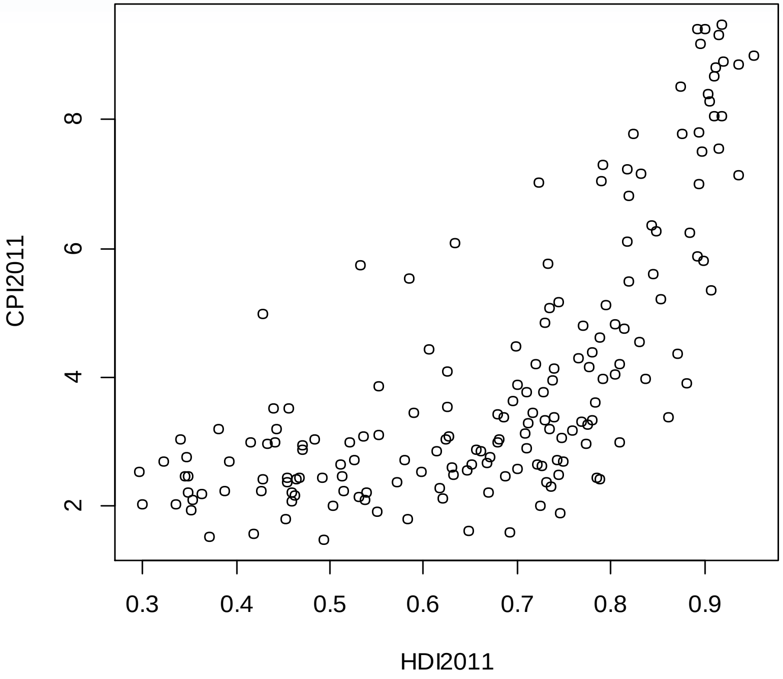
Fit Line

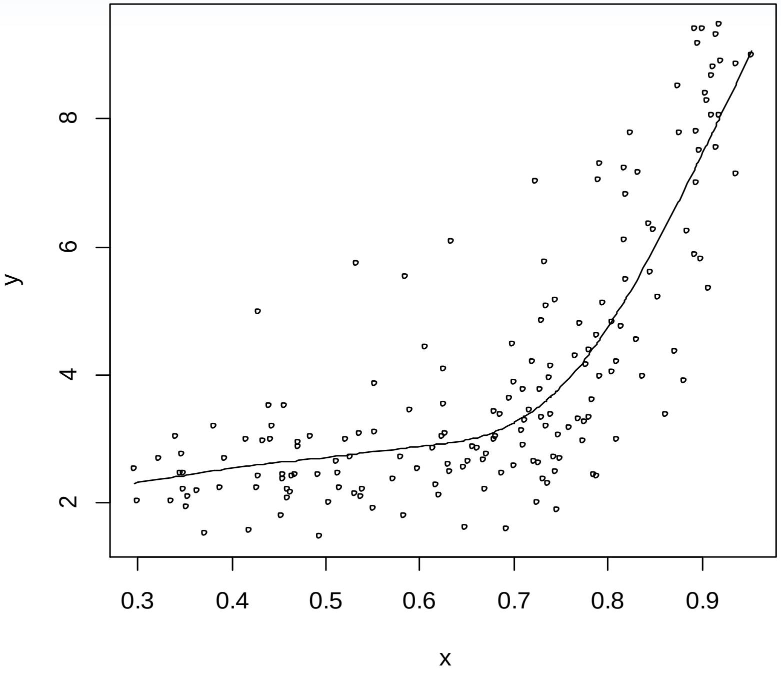
CPI=Corruption perception index (Transparency International)



Fit Line

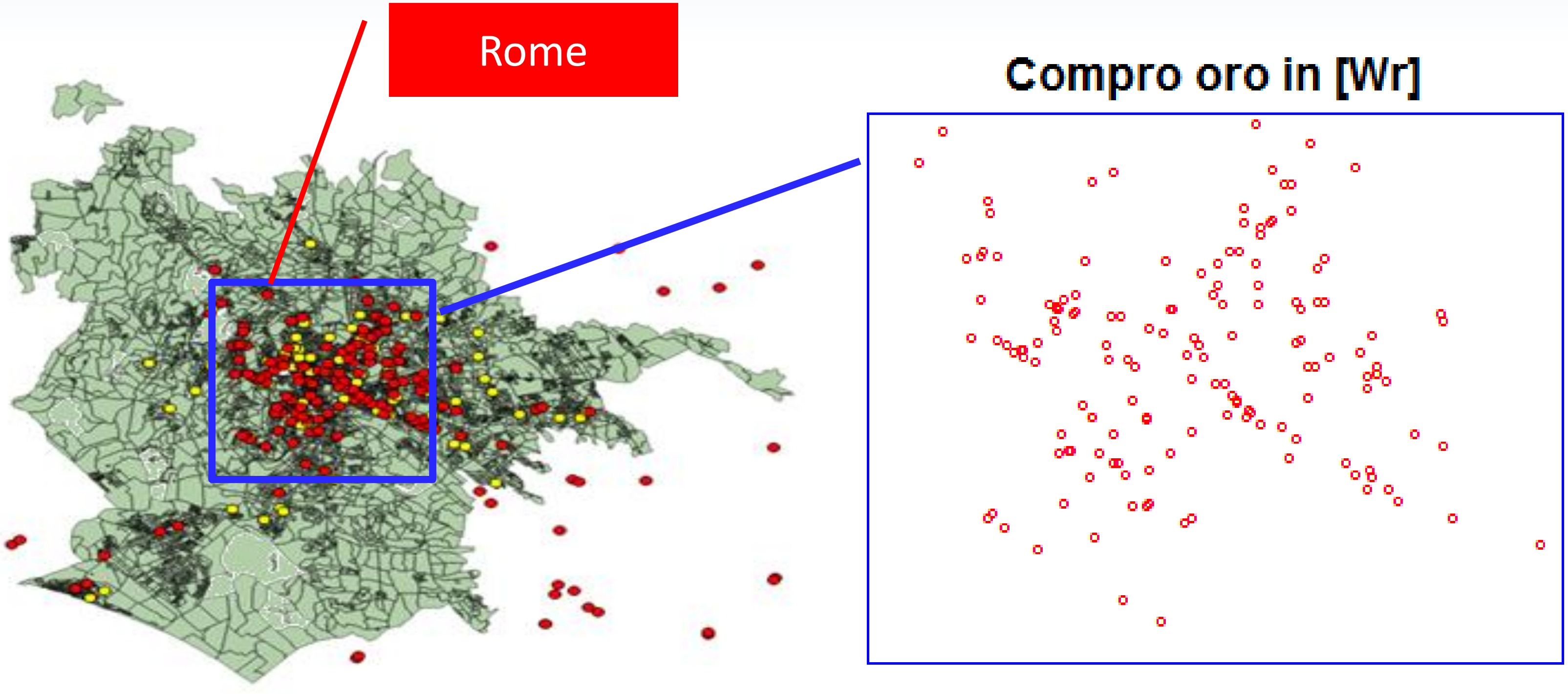
CPI=Corruption perception index (Transparency International)
HDI=Human Development Index





Fit Line

During the economic crisis, "buy gold" shops appeared in many Italian cities.



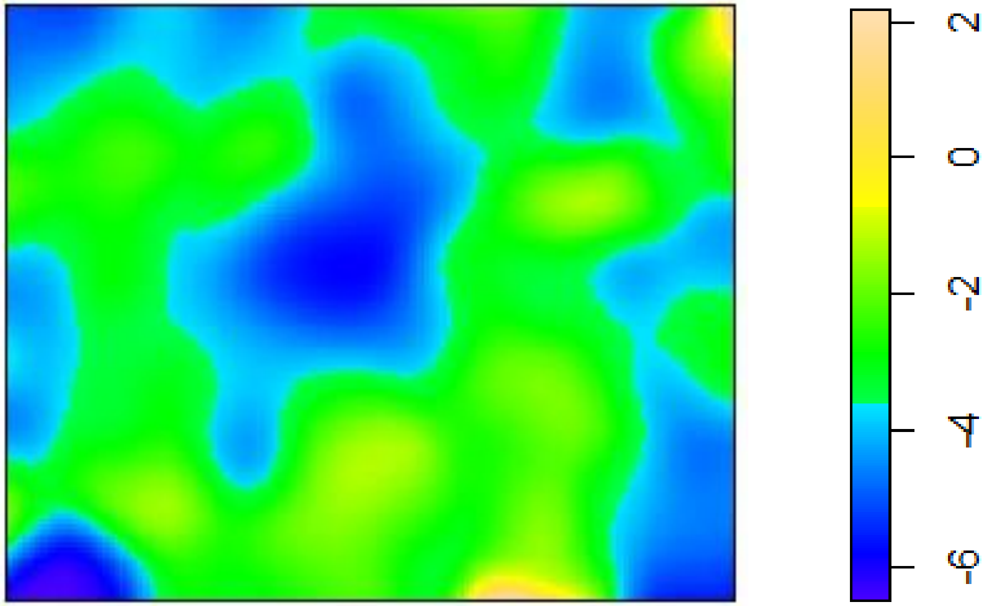
Rome

Compro oro in [Wr]

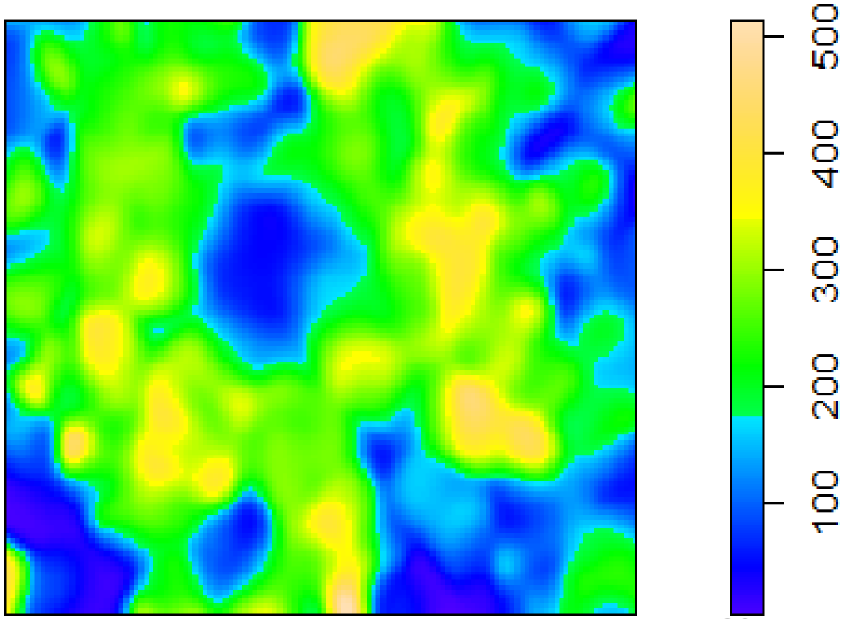
Fit distribution

Distribution of some variables on the territory (Rome) to also have a visual approach to understanding the possible relationships between distribution of points and characteristics of the territory.

Debts distribution



Population distribution



DATA RegHome

Sample size = 67

- **Price**=Home selling price in hundreds of dollars.
- **SQFT**=Square feet of living space
- **Ag**e=Age of home (years)
- **Feats**=Features Number out of 11 features (dishwasher, refrigerator, microwave, disposer, washer, intercom, skylight(s), compactor, dryer, handicap fit, cable TV access)
- **NE**=Located in northeast sector of city (1) or not (0)
- **COR**=Corner location (1) or not (0)

DATA Explore univariate – Stata commands

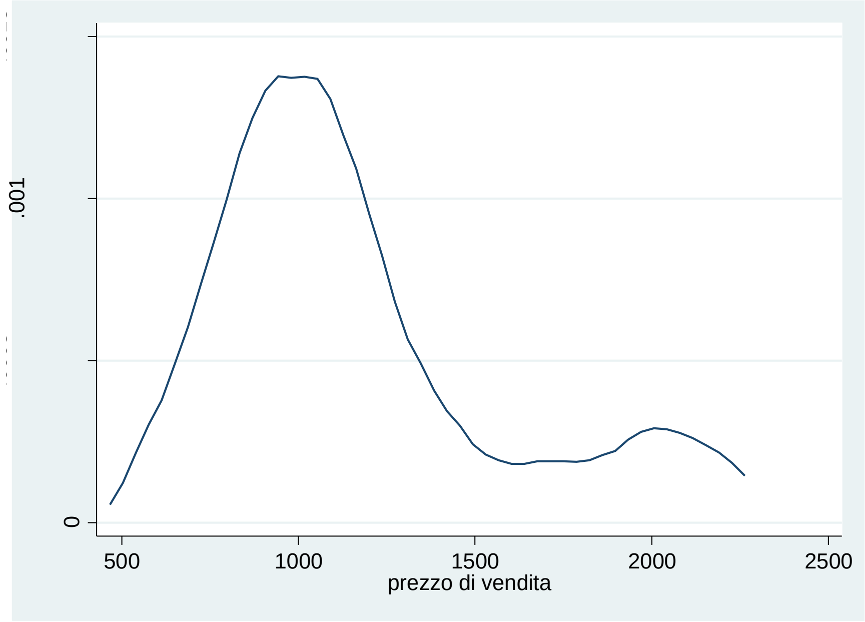
Descriptive statistics

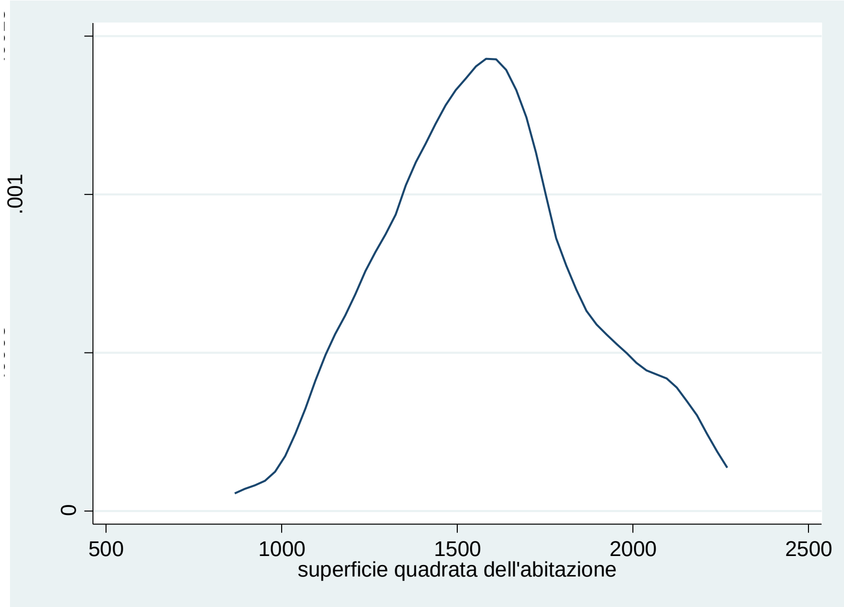
```
. sum price sqrt


 Variable |      Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       price |       67    1161.463    405.5376        580       2150
        sqft |       67    1582.112    278.7009        970     2165.5
```

DATA Explore univariate – Stata commands

Pdf Estimation

```
. kdensity price
. kdensity sqft
```

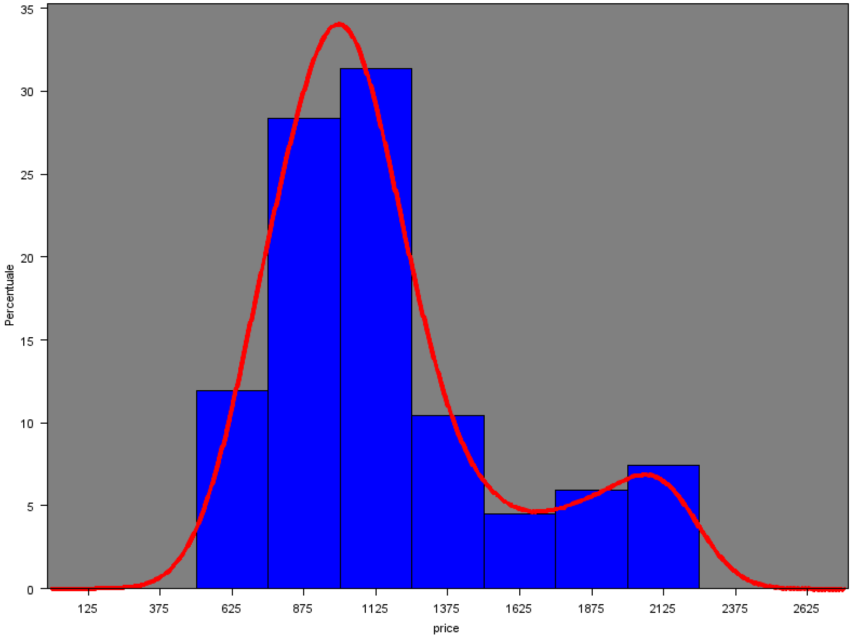


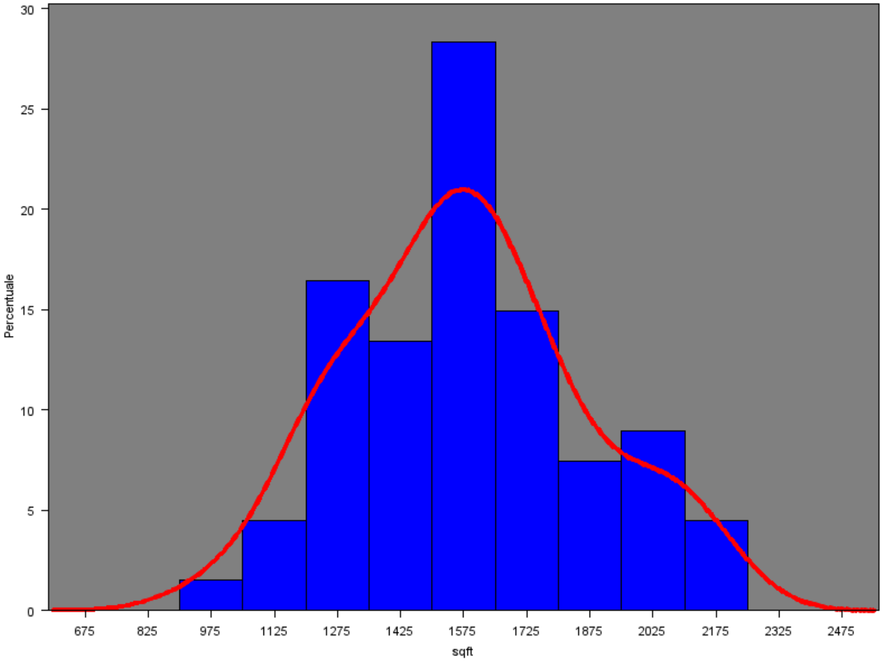


DATA Explore univariate – Stata commands

Pdf Estimation

```
. kdensity price
. kdensity sqft
```





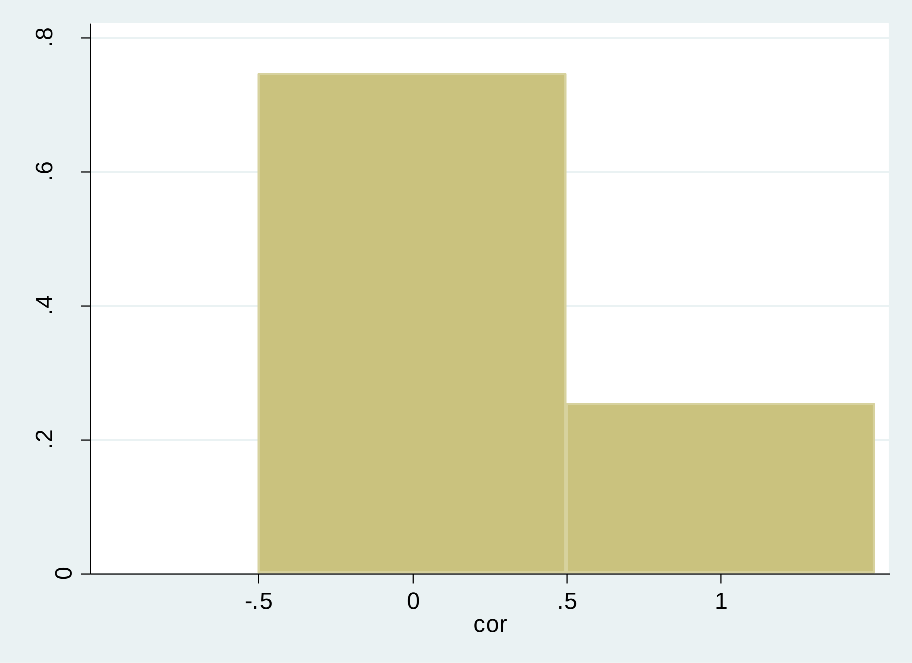
DATA Explore univariate – Stata commands

Descriptive statistics

```
. tab cor
```

```
   collocata|
sull'incroc |
  io di due |
    strade  |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |         50       74.63       74.63
          1 |         17       25.37      100.00
------------+-----------------------------------
      Total |         67      100.00
```

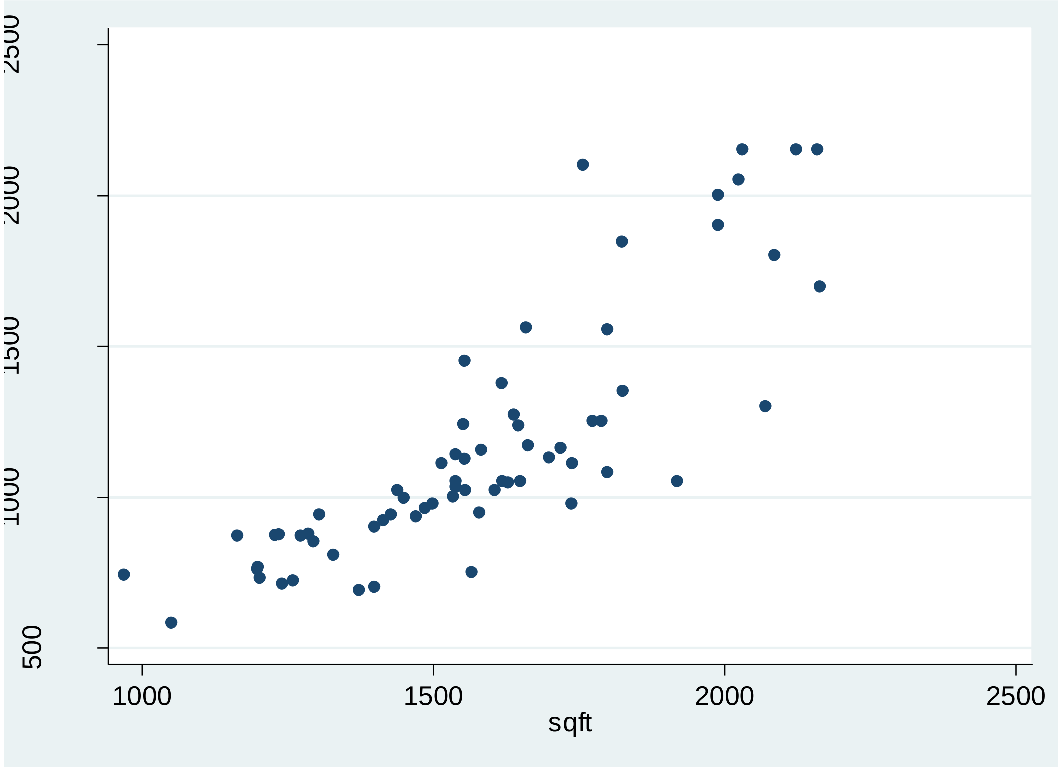
```
. hist cor, discrete
```



DATA Explore Bivariate – Stata commands

Descriptive statistics

```
. corr price sqft
. scatter price sqft
```



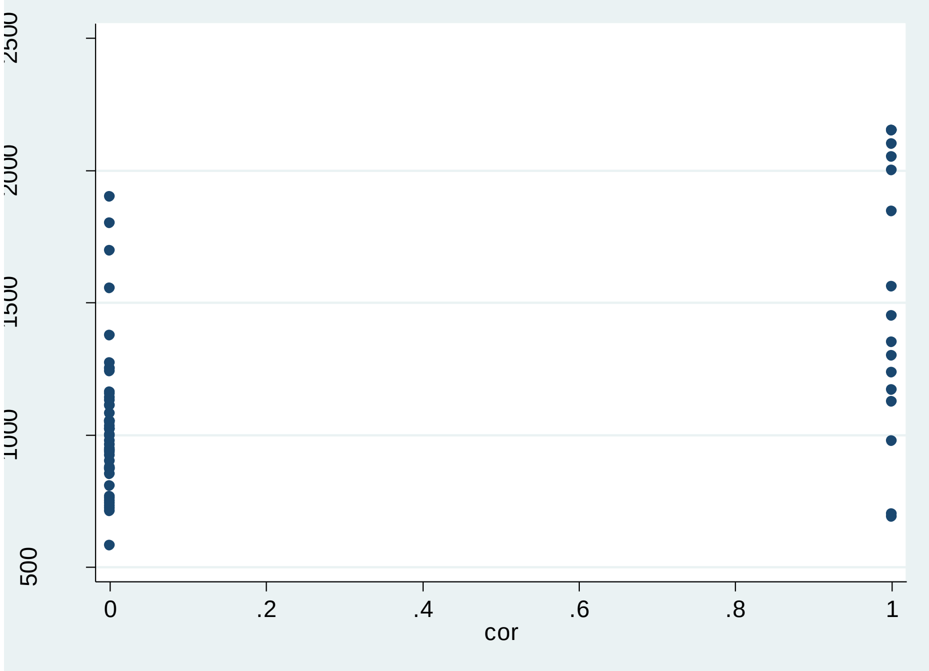
```
(obs=67)

             |    price     sqft
-------------+------------------
       price |   1.0000
        sqft |   0.8341   1.0000
```

DATA Explore Bivariate – Stata commands

Descriptive statistics

```
. sort cor
. by cor: sum price
. scatter price cor
```

```
--------------------------------------------------------------------------------
-> cor = 0
  Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
     price |        50     1036.46    268.4092        580       1900
--------------------------------------------------------------------------------
-> cor = 1
  Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
     price |        17    1529.118    515.0911        690       2150
```

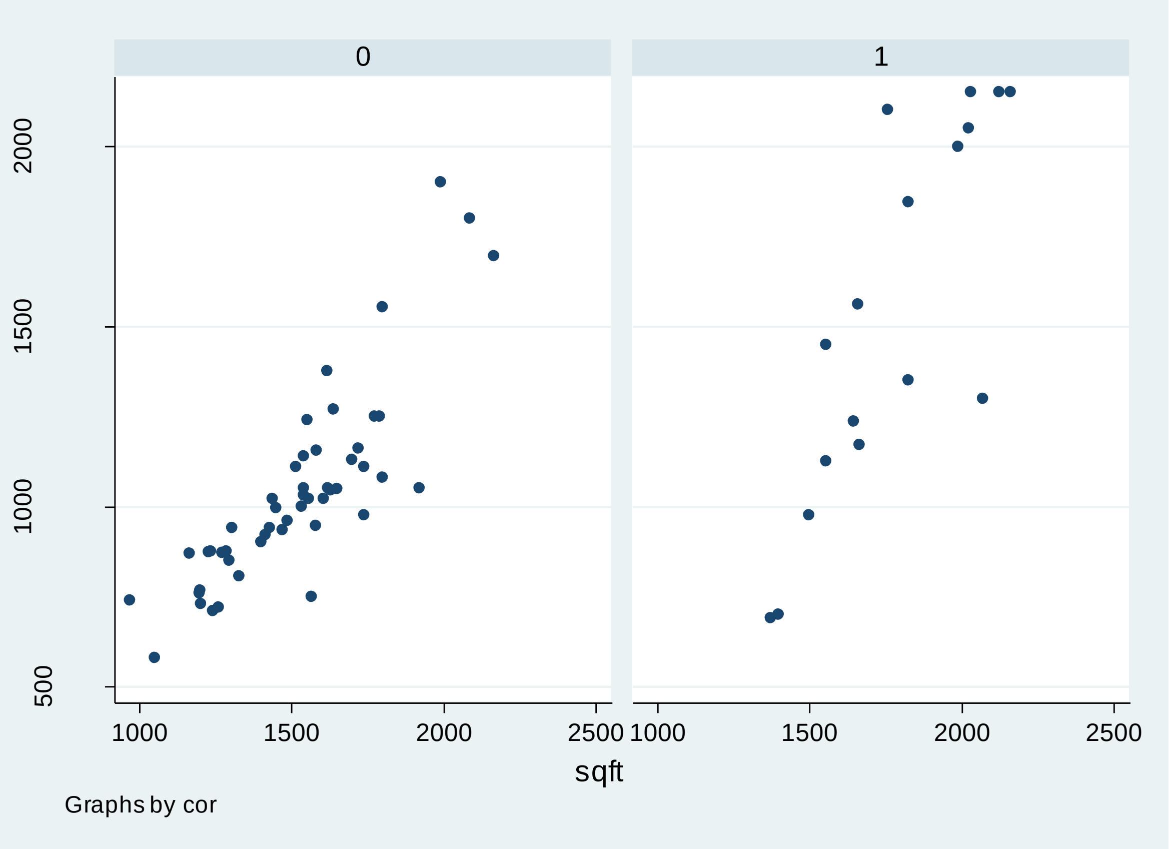


If the house is in the corner the price increases

DATA Explore Bivariate – Stata commands

Descriptive statistics

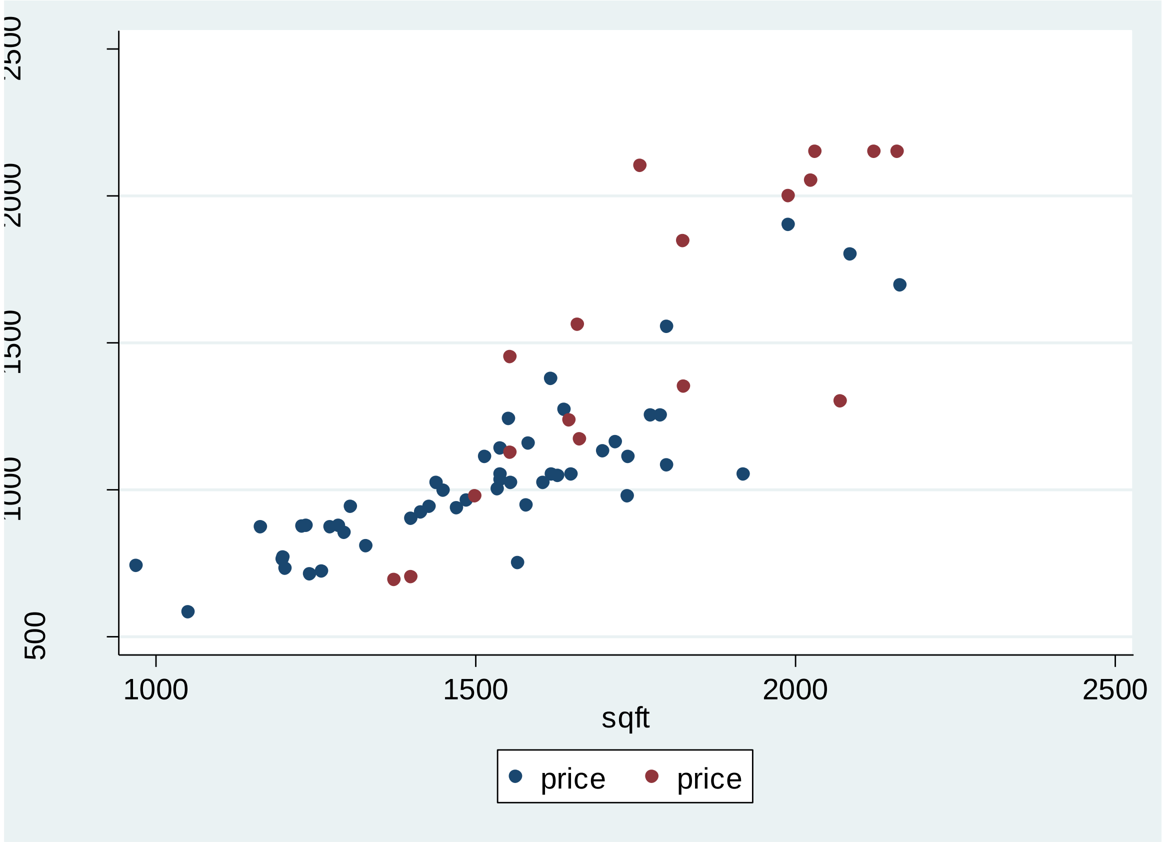
```
sort cor
by cor: corr price sqft
scatter price sqft, by(cor)
```



DATA Explore Bivariate – Stata commands

Descriptive statistics

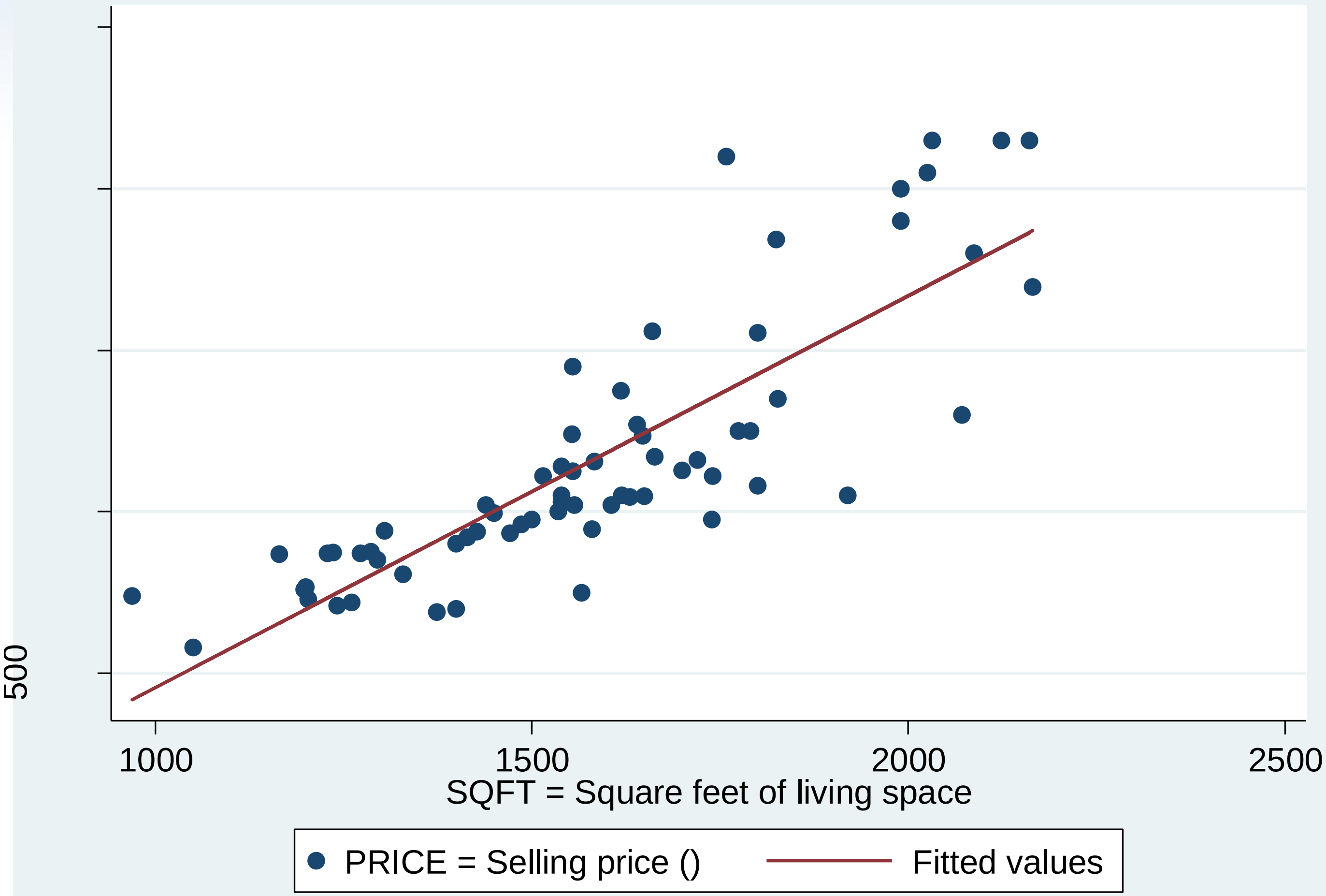
twoway (scatter price sqft if cor==0) (scatter price sqft if cor==1)
by cor: reg price sqft



DATA Explore Bivariate – Stata commands

```
-------------------------------------------------------------------------------
-> cor = 0
     Source |       SS       df       MS                Number of obs =      50
-------------+------------------------------            F(  1,    48) =  120.32
      Model |  2523442.92     1  2523442.92             Prob > F      =  0.0000
   Residual |   1006687.5    48  20972.6563             R-squared     =  0.7148
-------------+------------------------------            Adj R-squared =  0.7089
      Total |  3530130.42    49   72043.478             Root MSE      =  144.82
------------------------------------------------------------------------------
      price |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       sqft |   .8840891   .0805983    10.97   0.000     .7220353    1.046143
      _cons |  -304.4202   123.9457    -2.46   0.018    -553.6296   -55.21076
------------------------------------------------------------------------------
-------------------------------------------------------------------------------
-> cor = 1
     Source |       SS       df       MS                Number of obs =      17
-------------+------------------------------            F(  1,    15) =   33.23
      Model |  2924967.32     1  2924967.32             Prob > F      =  0.0000
   Residual |  1320134.44    15  88008.9628             R-squared     =  0.6890
-------------+------------------------------            Adj R-squared =  0.6683
      Total |  4245101.76    16   265318.86             Root MSE      =  296.66
------------------------------------------------------------------------------
      price |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       sqft |   1.665617   .2889202     5.76   0.000     1.049798    2.281435
      _cons |  -1426.617     517.73    -2.76   0.015    -2530.132   -323.1014
------------------------------------------------------------------------------
```

regression


500
1000
1500
2000
2500
SQFT = Square feet of living space
● PRICE = Selling price ()
Fitted values

Example – Output

```
. reg  price age feats ne cor sqft

 Source |       SS         df       MS          Number of obs =      67
--------+------------------------------         F(  5,     61) =   43.54
  Model |  8478759.27       5  1695751.85       Prob > F      =  0.0000
  Resid |  2375649.38      61  38945.0718       R-squared     =  0.7811
--------+------------------------------         Adj R-squared =  0.7632
  Total |  10854408.7      66  164460.737       Root MSE      =  197.35

------------------------------------------------------------------
  price |      Coef.   Std. Err.      t     P>|t|    [95% Conf.Interval]
--------+---------------------------------------------------------
    age | age of the building
  feats | number of options (reception, parking, garden,…)
     ne | if the house is in the north side (1) or not (0)
    cor | if the house is in the corner of building (1) or not (0)
   sqft | square feet of living space
  _cons | intercept
------------------------------------------------------------------
```

Example – Output

```
. reg  price age feats ne cor sqft

Source |       SS        df       MS          Number of obs =      67
-------+-----------------------------         F(  5,     61) =   43.54
 Model |  8478759.27      5  1695751.85       Prob > F      =  0.0000
 Resid |  2375649.38     61  38945.0718       R-squared     =  0.7811
-------+-----------------------------         Adj R-squared =  0.7632
 Total |  10854408.7     66  164460.737       Root MSE      =  197.35

-----------------------------------------------------------------
 price |      Coef.  Std. Err.     t    P>|t|    [95% Conf.Interval]
-------+---------------------------------------------------------
   age | -5.712149  2.121296  -2.69   0.009  -9.953942  -1.470356
 feats |  4.935951  21.39437   0.23   0.818  -37.84473   47.71663
    ne |  146.4015  60.79612   2.41   0.019   24.83218   267.9709
   cor |  191.3786  61.85902   3.09   0.003   67.68387   315.0734
  sqft |  .9871056  .1010516   9.77   0.000   .7850405   1.189171
 _cons | -478.1104  162.0919  -2.95   0.005  -802.2331  -153.9876
-----------------------------------------------------------------
```