

Outlier detection and treatment

LECTURE 12

Today is mainly about outliers

- 1) **Definitions**
What do we mean by an outlier, exactly?
- 2) **Motivation**
Do outliers really matter?
- 3) **Detection**
How to detect outliers?
- 4) **Treatment**
How to deal with outliers?

Definitions

What is an outlier?

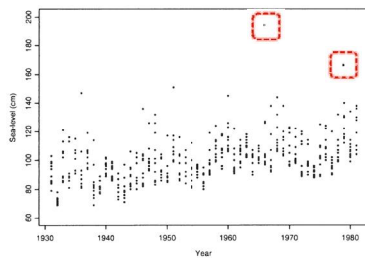
- An outlier is an observation “that appears to deviate markedly from other members of the sample in which it occurs” (Grubbs, 1969)
- Note: we focus on **univariate** outliers, those found when looking at a distribution of values in a single dimension (e.g. income).

Outliers in Statistical Data

VIC BARBETT
Chairman of English
and
TERRY LEWIS
Director of IAS

Allen Wilby & Sons
A Division of H&M

Highest sea-levels in Venice



Other classical definitions

- An outlier is “an observation that deviates so much from other observations as to arouse **suspicion** that it was generated by a different mechanism” (Hawkins 1980)
- Aguinis et al (2013) provide 14 definitions of outliers based on a literature review of 28 papers.

What causes outliers?

- **Human errors**, e.g. data entry errors
- **Instrument errors**, e.g. measurement errors
- **Data processing errors**, e.g. data manipulation
- **Sampling errors**, e.g. extracting data from wrong sources
- **Not an error**, the value is extreme, just a 'novelty' in the data

A dilemma

- Outliers can be genuine values
- The trade-off is between the loss of **accuracy** if we throw away "good" observations, and the **bias** of our estimates if we keep "bad" ones
- The challenge is twofold:
 1. to figure out whether an extreme value is good (genuine) or bad (error)
 2. to assess its impact on the statistics of interest

Do outliers matter?

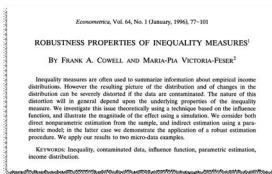
Theory first

Three papers:

- I. 1996a
Frank Cowell and Maria-Pia Victoria-Feser
- II. 2007
Frank Cowell and Emmanuel Flachaire (*)
- III. 1996b
Frank Cowell and Maria-Pia Victoria-Feser

Outliers and inequality measures – I

Cowell and Victoria-Feser (1996a)

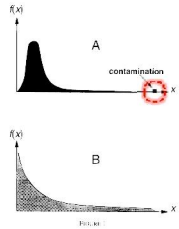


- This is a beautiful paper
- Explains why outliers (contaminants) are a serious threat to most inequality measures.
- “if the mean has to be estimated from the sample then all scale independent or translation independent and decomposable measures have an unbounded influence function” (p. 89)
- An unbounded IF is a catastrophe.

*The influence function

- F Ideal data, no contaminants
- $Gini_{TRUE} = I(F)$ “true” Gini index
- $G = (1 - \delta)F + \delta H$ Real-world data, with $\delta\%$ contaminants
 $0 \leq \delta \leq 1$
- $Gini_{ESTIMATED} = I(G)$ estimated Gini index
- The influence function, IF: $IF = \lim_{\delta \rightarrow 0} \frac{I(G) - I(F)}{\delta}$

The catastrophe



- Suppose the shape of the income distribution is represented by the continuous frequency distribution in part **A**
- Suppose that in the sample there are some rogue observations represented by the point mass labelled "**contamination**".
- Then, according to inequality statistics that are sensitive to the top end of the distribution, the income distribution in **A** will be **indistinguishable** from that represented in **B** (that is, IF is unbounded).

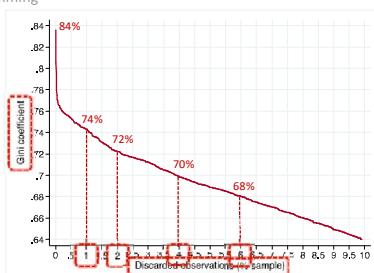
In practice

Hlasny and Verme (2018: 191)

- Many researchers routinely **trim** outliers or problematic observations or apply **top coding** with little consideration of the implications for the measurement of inequality
- One example to illustrate

Sensitivity of the Gini index to extreme values

iterative trimming



***Outliers and inequality measures – II**
Cowell and Flachaire (2007)



- Explains how and why **outliers** are a serious **threat** to most inequality measures.



***How rapidly the catastrophe occurs**
Rates of increase to infinity of the influence function

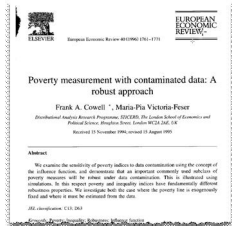
- Let us concentrate only on the extremes of the income distribution. Data contamination can occur at **very high incomes** (say at a point z that **approaches infinity**) or at **very low incomes** ($z = 0$).

Measure	Generalised entropy, I_α^z			Atkinson, I_A			LogVar	Gini
	$\alpha > 1$	$0 < \alpha \leq 1$	$\alpha = 0$	$\alpha < 0$	$0 < \epsilon < 1$	$\epsilon = 1$		
$z \rightarrow \infty$	z^α	z	z	z	z	z	z	z
$z \rightarrow 0$	$z^{-\alpha}$	$-\log z$	z	z	$-\log z$	$z^{1-\epsilon}$	$(\log z)^2$	z

- Result 1:** GE measures with $\alpha > 1$ are very sensitive to high incomes in the data.
- Result 2:** GE measures with $\alpha < 0$, and Atkinson measures with $\epsilon > 1$ are very sensitive to small incomes in the data.
- We will return on this **catastrophe** in due time, later during this workshop.



Outliers and poverty measures
Cowell and Victoria-Feser (1996b)



- Explains why **outliers only rarely** are a serious **threat** to most poverty measures.
- Poverty measures are not sensitive to the values (real or contaminated) of the incomes of the rich



Recap

- The answer to the question on whether outliers matter **depends** on the statistic of interest
- **Inequality**: both theory (unbounded IF) and practice (incremental truncation) suggest that they matter (tremendously). Not taking this issue into proper account puts inequality comparisons at risk.
- **Poverty**: not so much

How to detect outliers?

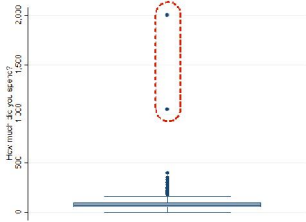
Visual inspection

- Our procedures are part **graphical**, and part **automatic**. For each commodity, we draw histograms and one-way plots of the logarithms of the unit values, using each to detect the presence of gross outliers for further investigations. [...] [Automatic method] **does not remove the need** for the graphical inspection (Deaton and Tarozzi 2005)

Visual inspection

Malawi IHS3, Cassava tuber expenditure

- Example 3: use graphical diagnostic tools, e.g. the boxplot graph

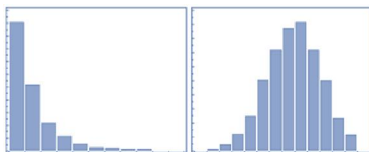


Statistical methods

- The literature is rich with methods to identify outliers; in practice, most methods used in empirical work hinge on the underlying [distribution of the data](#).
- The idea is simple:
 - transform the variable to induce normality
 - set thresholds to identify extreme values

Transform the variable to induce normality

- The easiest transformation relies on taking the [logarithm](#) of the variable of interest
- The log “squeezes” large values more, so that skewed distributions become more symmetrical and closer to a Normal distribution.

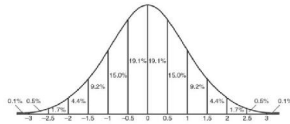


Set a threshold

- We must specify a **threshold** for deciding whether each observation is 'too extreme' (outlier or not?)
- Common '**thumb-rule**' thresholds : an observation is considered an outlier if it is more than **2.5, 3, 3.5 standard deviations far from the mean** of the distribution
- In formulas: x is an outlier if $x > \bar{x} + z_\alpha s$
 where z_α equals, say, 2.5.
- We can express the same criterion as $\frac{x - \bar{x}}{s} > z_\alpha$
 where the left-hand side is called a **z-score** (a variable with mean = 0 and var = 1)

Why 2.5, 3, or any other number?

- Under the assumption of normality:



- $z_\alpha = 2.5$ implies that outliers are in the region where $\alpha = 0.0062$ percent of other observations normally are.

Deaton and Tarozzi (2005)

THE GREAT INDIAN POVERTY DEBATE

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Poverty and Poverty in India

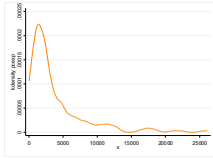
Abstract: This paper examines the distribution of household consumption expenditures in India, and finds that the distribution is highly skewed, with a long tail of poor households. The distribution is also highly volatile, with a large fraction of households in the tail of the distribution. The paper discusses the implications of these findings for the design of social safety nets and other poverty reduction programs.

In the case of **India**, D&T (2005) flagged as outliers prices whose logarithms exceeded the mean of logarithms by more than 2.5 standard deviations:

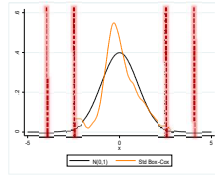
$$\frac{\ln(x) - E[\ln(x)]}{sd[\ln(x)]} > 2.5$$

Transformation and thresholds

Raw untransformed data



Transformed data



Two questions

- 1) How good is such an approach?
- 2) What to do after flagging outliers?



How good is such an approach?

- Log-transformation is very basic – how to deal with negative values?
- Not recommended when the log-distribution can not be assumed to be a Normal distribution
- Why should we set the threshold using the **mean** and **standard deviation**, which are sensitive to extreme values, if this is exactly what we are worried about?

$$\frac{\ln(x) - E[\ln(x)]}{sd[\ln(x)]} > 2.5$$

- We can do better



*The Box-Cox transformation

Building a household consumption database for the calculation of poverty PPPs

Technical note

DRAFT 1.0

Oliver Dupuis, World Bank
March 2007

- The Box-Cox transformation:

$$y_h^{(\lambda)} = \begin{cases} (y_h^\lambda - 1)/\lambda & \text{if } \lambda \neq 0 \\ \ln y_h & \text{if } \lambda = 0 \end{cases}$$

- The transformed variable is often remarkably close to a Normal dn.
- Outliers are identified if:
 $y_h > 75\text{th percentile} + 5 \times \text{IQR}$

*The Box-Cox method: An assessment

- Only applies to **strictly positive variables** (e.g., it does not necessarily work with income)
- Calculation is cumbersome, and often problematic

A popular strategy

robustification

- While there is no agreement on the best method, a common solution is to use **robust measures of scale** and **location** to set the threshold for flagging outliers
- the idea is to replace the sample average \bar{x} with a robust estimator (e.g. the median), and the standard deviation s with a robust estimator. A popular option is the median absolute deviation (MAD).

The median absolute deviation (MAD)

$$z_h = \frac{x_h - \bar{x}}{s}$$

$$z_h = \frac{|x_h - \text{med}[x_h]|}{\text{MAD}}$$

$$\text{MAD} = b \times \text{med}|x - \text{med}[x]|$$

$$b = 1.4826$$

if the distribution is Gaussian



We can do better

Rousseeuw and Croux (1993, JASA)

Alternatives to the Median Absolute Deviation

Peter J. Rousseeuw and Christophe Croux*

In robust estimation one frequently needs an initial or auxiliary estimate of scale. For this one usually takes the median absolute deviation $\text{MAD}_n = 1.4826 \text{ med}\{|x_i - \text{med}(x_i)|\}$, because it has a simple explicit formula, needs little computation time, and is very robust as witnessed by its bounded influence function and its 50% breakdown point. But there is still room for improvement in two areas: the fact that MAD_n is aimed at symmetric distributions and its low (37%) Gaussian efficiency. In this article we set out to construct explicit and 50% breakdown scale estimators that are more efficient. We consider the estimator $S_n = 1.1926 \text{ med}\{\text{med}\{|x_i - x_j|\}\}$ and the estimator Q_n given by the 25 quantile of the distances $\{|x_i - x_j|; i < j\}$. Note that S_n and Q_n do not need any location estimate. Both S_n and Q_n can be computed using $O(n \log n)$ time and $O(n)$ storage. The Gaussian efficiency of S_n is 58%, whereas Q_n attains 52%. We study S_n and Q_n by means of their influence functions, their bias curves (for imprecision as well as explosion), and their finite-sample performance. Their behavior is also compared at non-Gaussian models, including the negative exponential model where S_n has a lower gross-error sensitivity than the MAD_n .

KEY WORDS: Bias curve; Breakdown point; Influence function; Robustness; Scale estimation



Rousseeuw and Croux (1993)

Rousseeuw and Croux (1993) propose to substitute the MAD with a different estimator:

$$S = c \times \text{med}_i\{\text{med}_j\{|x_j - x_i|\}\}$$

For each i we compute the median of $\{|x_i - x_j|; (j = 1, \dots, n)\}$. This yields n numbers, the median of which gives our final estimate S .

$$z_h = \frac{|x_h - \text{med}[x_h]|}{S}$$

$c = 1.1926$ at the Gaussian model.



Recap

- “take the log and run” is not a recommended practice
- taking the log and robustifying the z-score is a better practice
- Belotti and Vecchi (2019) provide [outdetect.ado](#)

Malawi, 2013

Method	Overall	Left	Right
Z-score	2.08	0.20	1.88
MAD-score	3.05	0.35	2.70
S-score	3.02	0.35	2.67
Q-score	3.00	0.35	2.65

- ‘take the log and run’:
2.08% of outliers (most of which in the right tail)
- ‘take the log, robustify the z-score, and run’:
3.00% (most of which in the right tail)

How to deal with outliers?

(in one slide)

Treatment of outliers

Three main methods of dealing with outliers, apart from removing them from the dataset:

- 1) **reducing the weights** of outliers (trimming weight)
- 2) **changing the values** of outliers (Winsorisation, trimming, imputation)
- 3) **using robust estimation techniques** (M-estimation).

- Documentation, transparency & reproducibility



Lessons learned

- Outliers can be **genuine** observations... be gentle to the data and document each and every step of the data processing
- As far as inequality is concerned, outliers are the worst enemy (**unbounded IF**)
- Outlier detection:
 - go beyond the “**take the log and run**” strategy. It works well only if you can describe the data with a Gaussian distribution. Typically, however, distributions are skewed.
 - Use a “**take the log, robustify the z-score and run**”, strategy.
- **Outlier treatment**: it depends. Quantile regression is a good candidate.

References

Required readings

Barnett, V., & Lewis, T. (1994). Outliers in Statistical Data. 3rd edition. J. Wiley & Sons (Chapter 1 & 2)

Suggested readings

Avarez, E., Garcia-Fernández, R. M., Blanco-Encomienda, F. J., & Muñoz, J. F. (2014). The effect of outliers on the economic and social survey on income and living conditions. World Acad. Sci., Eng. Technol., Int. J. Soc., Behav., Educ., Econ., Bus. Ind. Eng., 8, 3276-3280.

Belotti, F., & Vecchi, G. (2019). Take the Log and Run: Outliers and Welfare Measurement, mimeo.

Cowell, F. A., & Flachaire, E. (2007). Income distribution and inequality measurement: The problem of extreme values. Journal of Econometrics, 141(2), 1044-1072.

Cowell, F., & Victoria-Feser, M. (1996). Robustness Properties of Inequality Measures. Econometrica, 64(1), 77-

Cowell, F. A., & Victoria-Feser, M. P. (1996). Poverty measurement with contaminated data: A robust approach. European Economic Review, 40(9), 1761-1771.

Deaton, A., & Cartwright, A. (2005). "Prices and Poverty in India." The Great Indian Poverty Debate. New Delhi: MacMillan.

Dupriez, O. (2007). Building a household consumption database for the calculation of poverty PPPs. Technical note. Available at: <http://go.worldbank.org/4YG75RGTO>.

Grubbs, F. E. (1969). Procedures for detecting outlying observations in samples. Technometrics, 11(1), 1-21.

Hlasny, V., & Verme, P. (2018). Top Incomes and Inequality Measurement: A Comparative Analysis of Correction Methods Using the EU SILC Data. Econometrics, 6(2), 30.

Mancini, G., & Vecchi, G. (2019). On the Construction of a Welfare Indicator for Inequality and Poverty Analysis, mimeo.

OECD (2013). OECD Guidelines for Micro Statistics on Household Wealth

Rousseeuw, P. J., & Croux, C. (1993). Alternatives to the median absolute deviation. Journal of the American Statistical association, 88(424), 1273-1283.

Thank you for your attention

Homework

Exercise 1 - Engaging with the literature

World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:10 No:10 2016

The Effect of Outliers on the Economic and Social Survey on Income and Living Conditions
Eduardó Álvarez, Rosa M. García Fernández, Francisco J. Blanco-Escrivido, Juan F. Muñoz

Abstract: The Economic and Social Survey on Income and Living Conditions (ESES) is a panel survey which provides information on income, poverty, social exclusion and quality of life of households and individuals in the European Union. The ESES data contains outliers which may cause biases in the estimation of income and living conditions. The objective of this paper is to study the effect of outliers on the estimation of income and living conditions in the ESES. The paper analyzes the effect of outliers on the estimation of income and living conditions in the ESES. The paper analyzes the effect of outliers on the estimation of income and living conditions in the ESES. The paper analyzes the effect of outliers on the estimation of income and living conditions in the ESES.

Summarize the main conclusions of the paper: do outliers matter? Why or why not?

Exercise 2 - Do-it-yourself....

English

Stata/R/SPSS/Excel/...

- 1) Generate a log-normal looking wealth distribution
- 2) Estimate the Gini index
- 3) Contaminate the distribution with a few extreme values
- 4) Re-estimate the Gini index

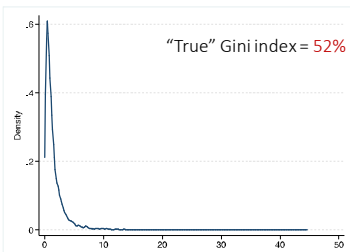
```
clear
set obs 5000
set seed 123456
gen ln = ln(rln(10,1))
gen ln = ln(ln)

* simulate order of magnitude mistakes
* take 100 obs around the median
* of the distribution and multiply
* them by 100

sort ln
gen ccont100 = 1
replace ccont100 = 100 in 2489/2520
gen ln_cont100 = ln+ccont100
```

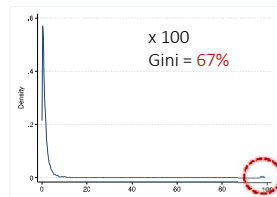
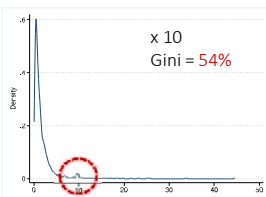


"True" distribution

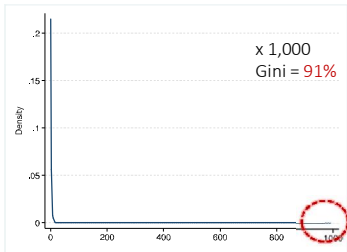


Contamination

40 out of 5,000 observations (less than 1%) are "contaminated"

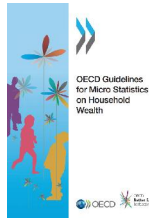


Contamination



Exercise 3 – Inequality measures

- Comment on table 7.3 from OECD (2013) p.172 (see next slide).
- What can you say about the sensitivity of estimates to the treatment of outliers?



Exercise 3 – Inequality measures

OECD (2013)

Table 7.3. Effect of the treatment of outliers on summary measures of wealth inequality in the United States, 2007

	Raw	Shave top and bottom 1%	Shave top 1% and bottom 0.5%
Mean	559 846	378 215	559 361
Median	123 780	123 780	123 800
Gini	0.82	0.74	0.81
SCV ²	18.1	2.4	14.6
P90/P10	30 000	3 359	3 061
P75/P25	28.3	24.5	24.3
P90/P50	7.6	7.0	7.4
n	4 418	3 698	4 359

Source: 2007 Survey of Consumer Finances.
