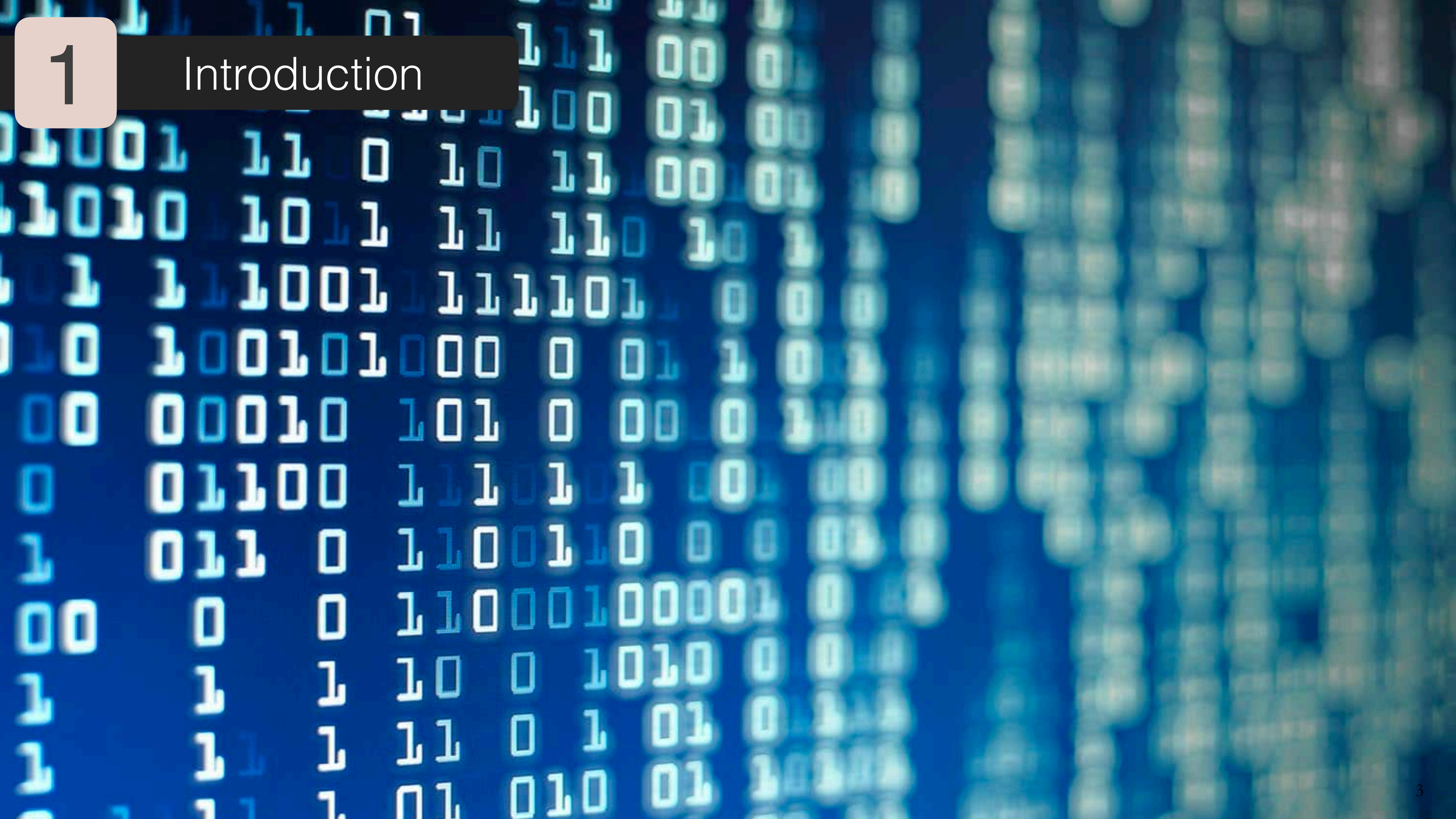
1

2

3



1 Introduction

1

Week 1: Scientific method

Week 2: Causal theorising

Week 3: Research design

Week 4: Concepts and measurement

Week 5: Surveys and sampling

1

Upon successful completion, students will have the knowledge and skills to:

1. explain the complexity of contemporary politics from the perspective of solid research design and empirical analysis;

2. apply a range of methodological approaches by which to analyse such issues;

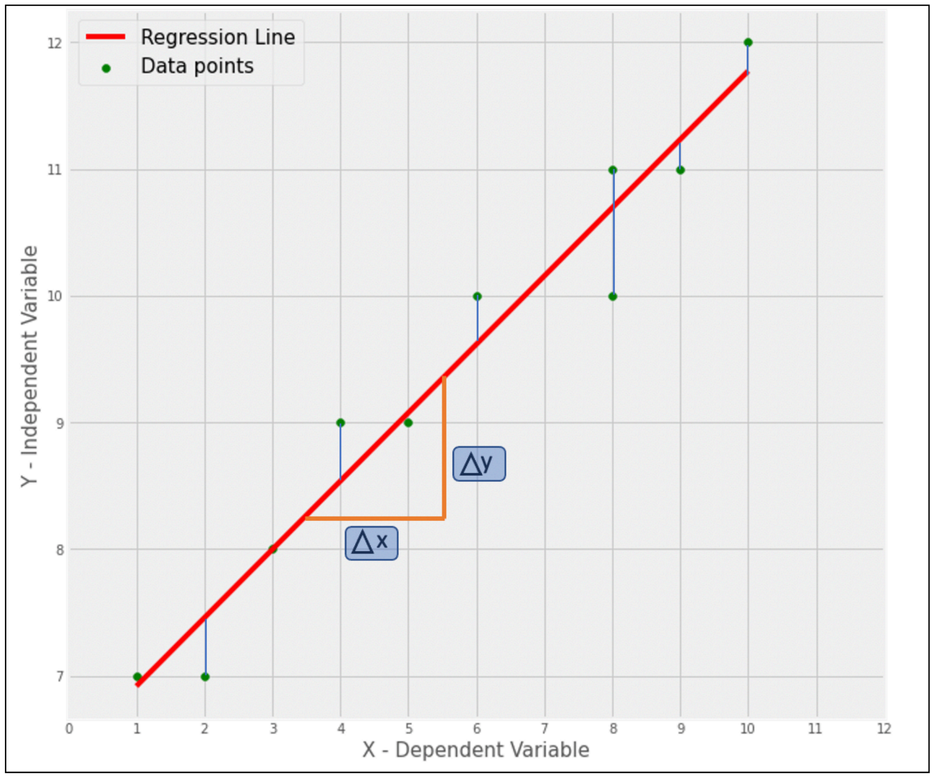
3. generate, explain, and visualise descriptive statistics and basic inferential statistics for political phenomena using a statistical software package; and

4. apply conceptual and analytical tools to a political phenomenon at a higher level of study or in a professional working environment.

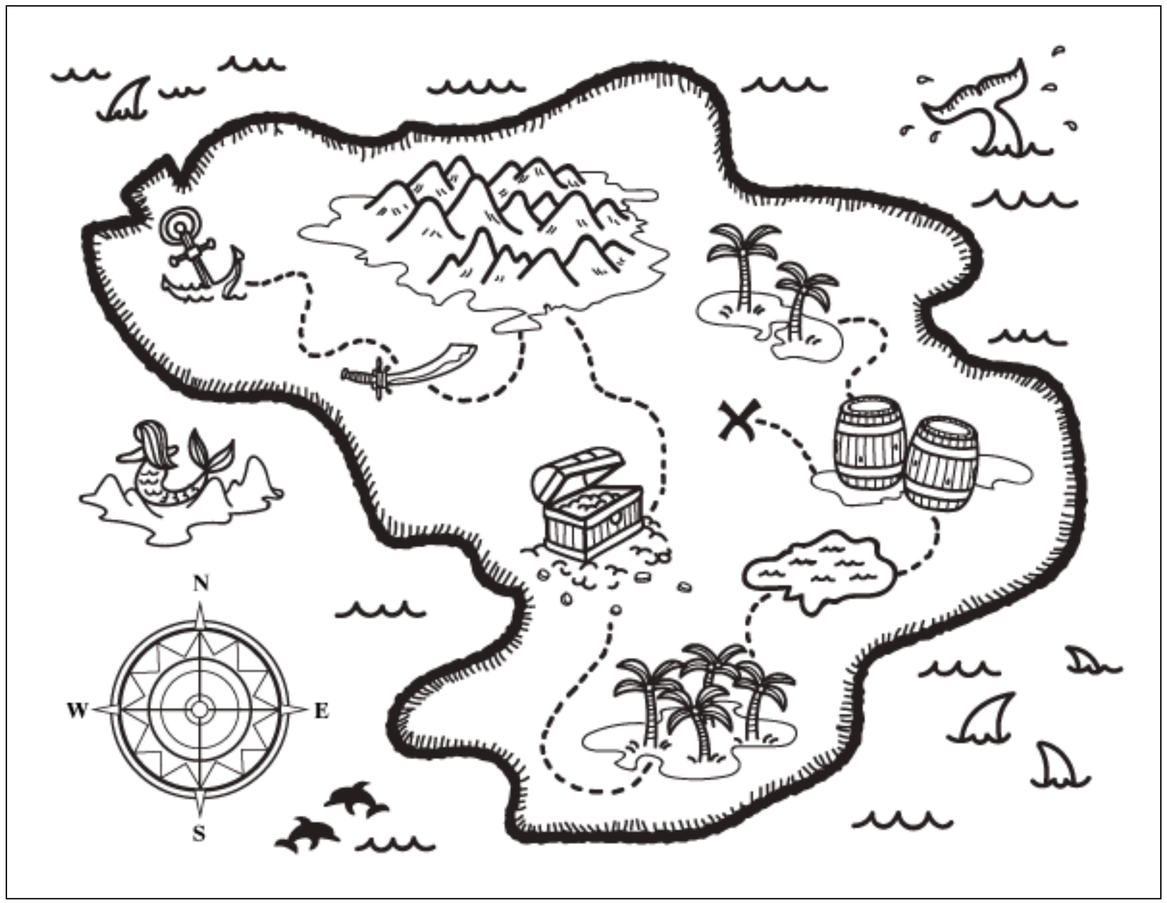
POLS2044 (2022) Course Guide | 2

1

$$Y = \alpha + \beta X + \epsilon + \varepsilon$$

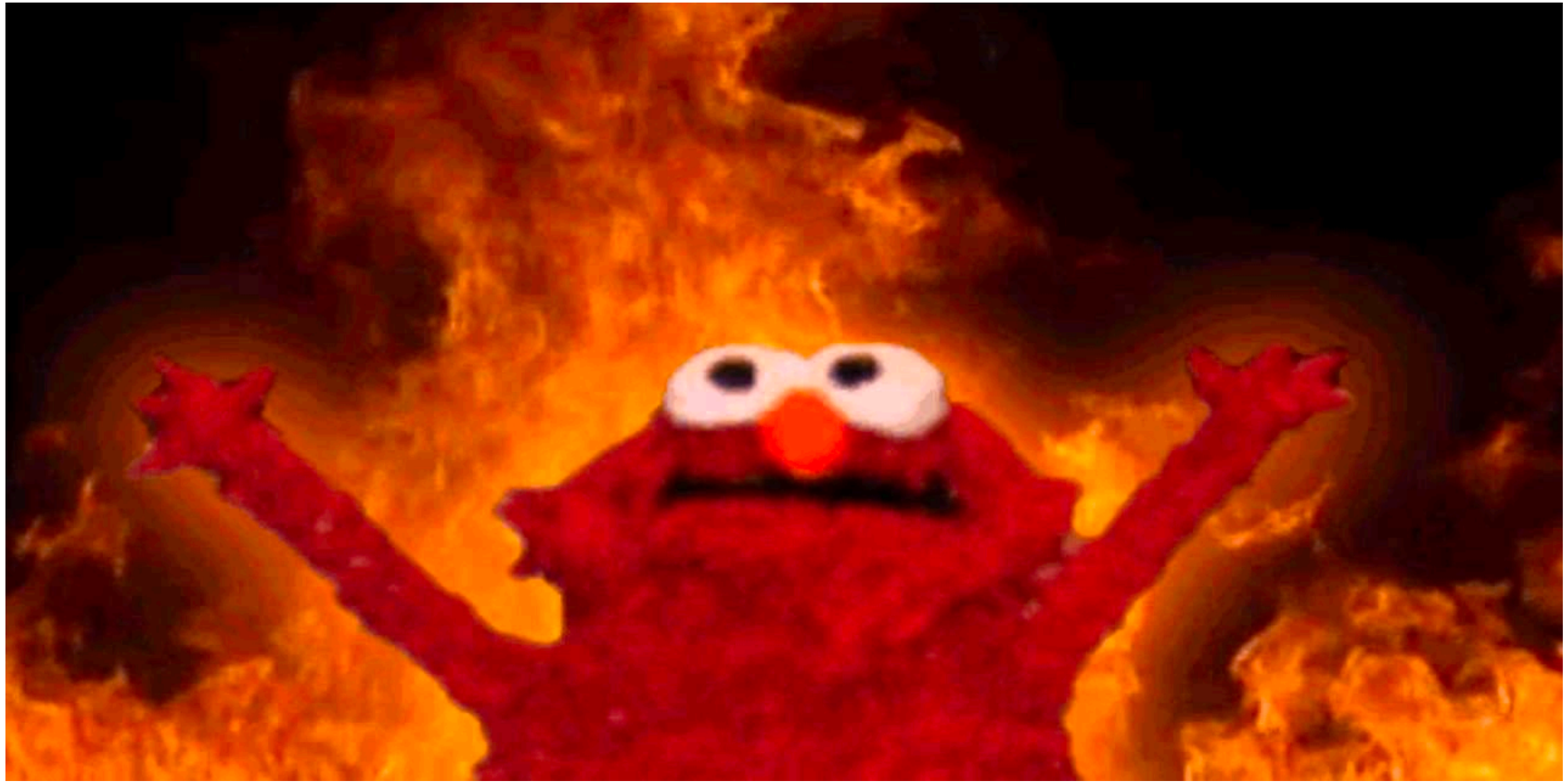


Source: https://towardsdatascience.com/linear-regression-explained-1b36f97b7572



There is often an easier map to quantitative analysis than qualitative analysis.

1



Source: https://static1.srcdn.com/wordpress/wp-content/uploads/2020/05/Elmo-Flames-Meme.jpg

1

$$Y = \alpha + \beta X + \epsilon + \varepsilon$$

Where:

Y is the **outcome** you are trying to explain.
X is the main **explanatory** variable.
α (alpha) is the intercept.
β (beta) is the estimated relationship between X and Y.
ϵ is the systematic error.
ε is the random error.

1

We will be coming back to this equation in a few weeks, but first we need to start by learning about our main **cause (X)** and **outcome (Y)** variables.

1

What can **descriptive inference** tell us that causal inference cannot?

What are the basic **descriptive statistics**?

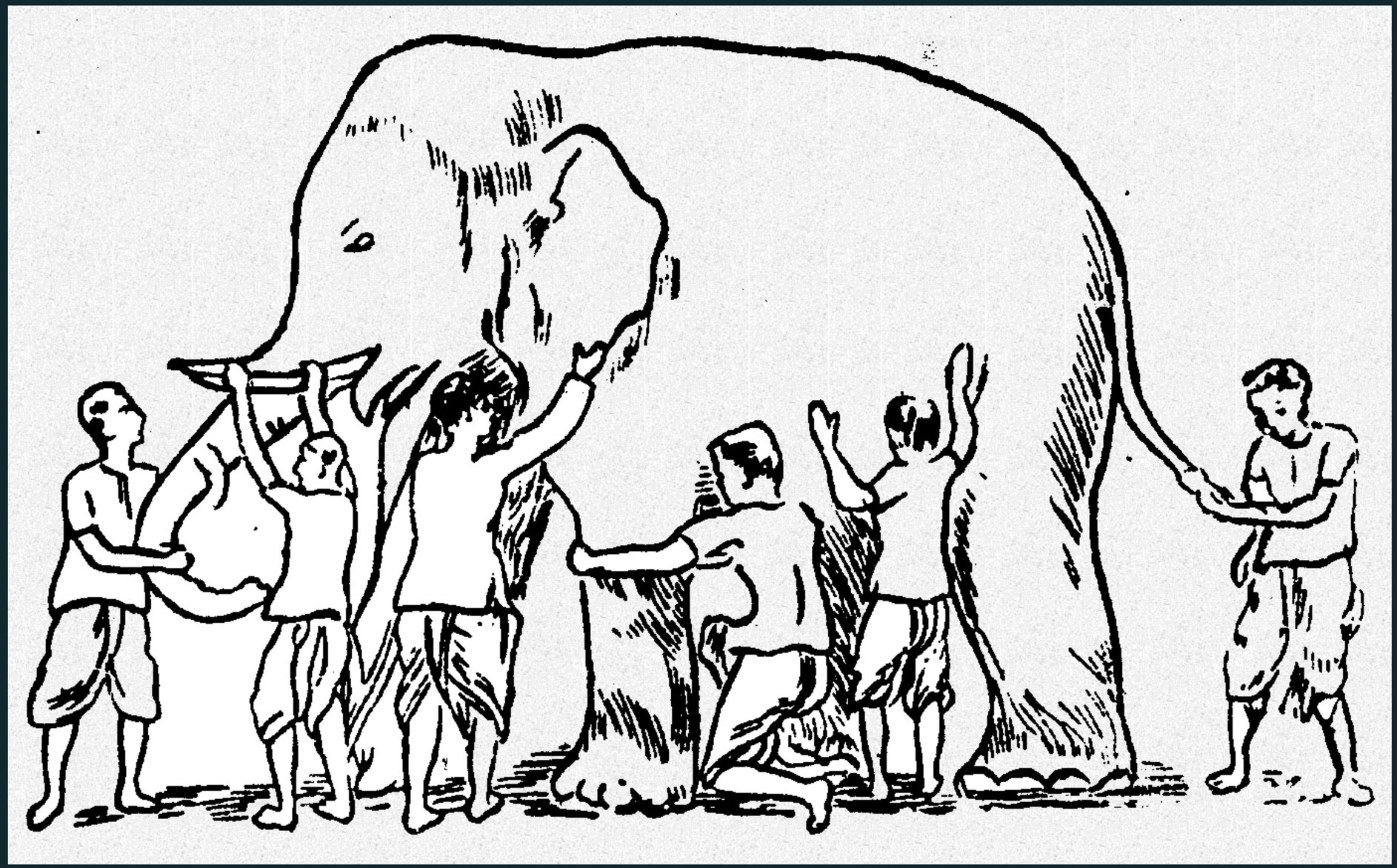
1

Political scientists spend much more time thinking about **causal inference** and **data** analysis than they think about **conceptualising** and **describing** their causes (X's) and outcomes (Y's).

However, the former is of limited utility without the latter.

Image source: https://imgflip.com/memetemplate/57007095/Wrong-tool-for-the-job

2 Descriptive inference



https://jainworld.com/education/jain-education-material/jain-stories/elephant-and-the-blind-men/

2

Most people use real-world data without thinking about **how they are generated** and **whether they capture what they think they do**.

2

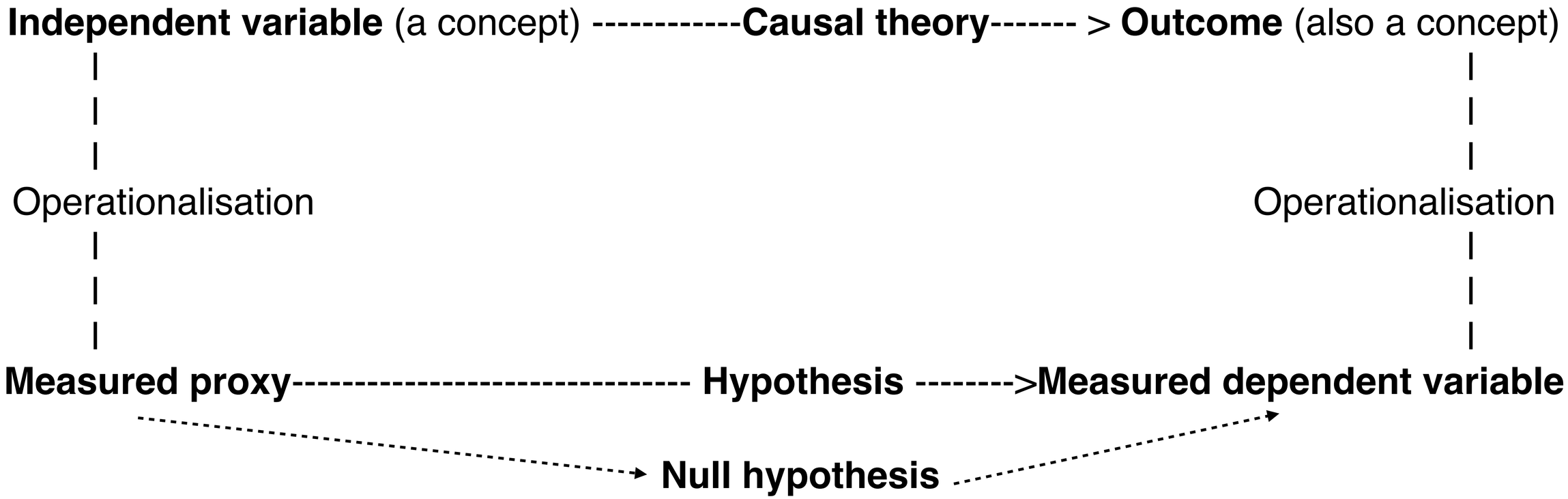
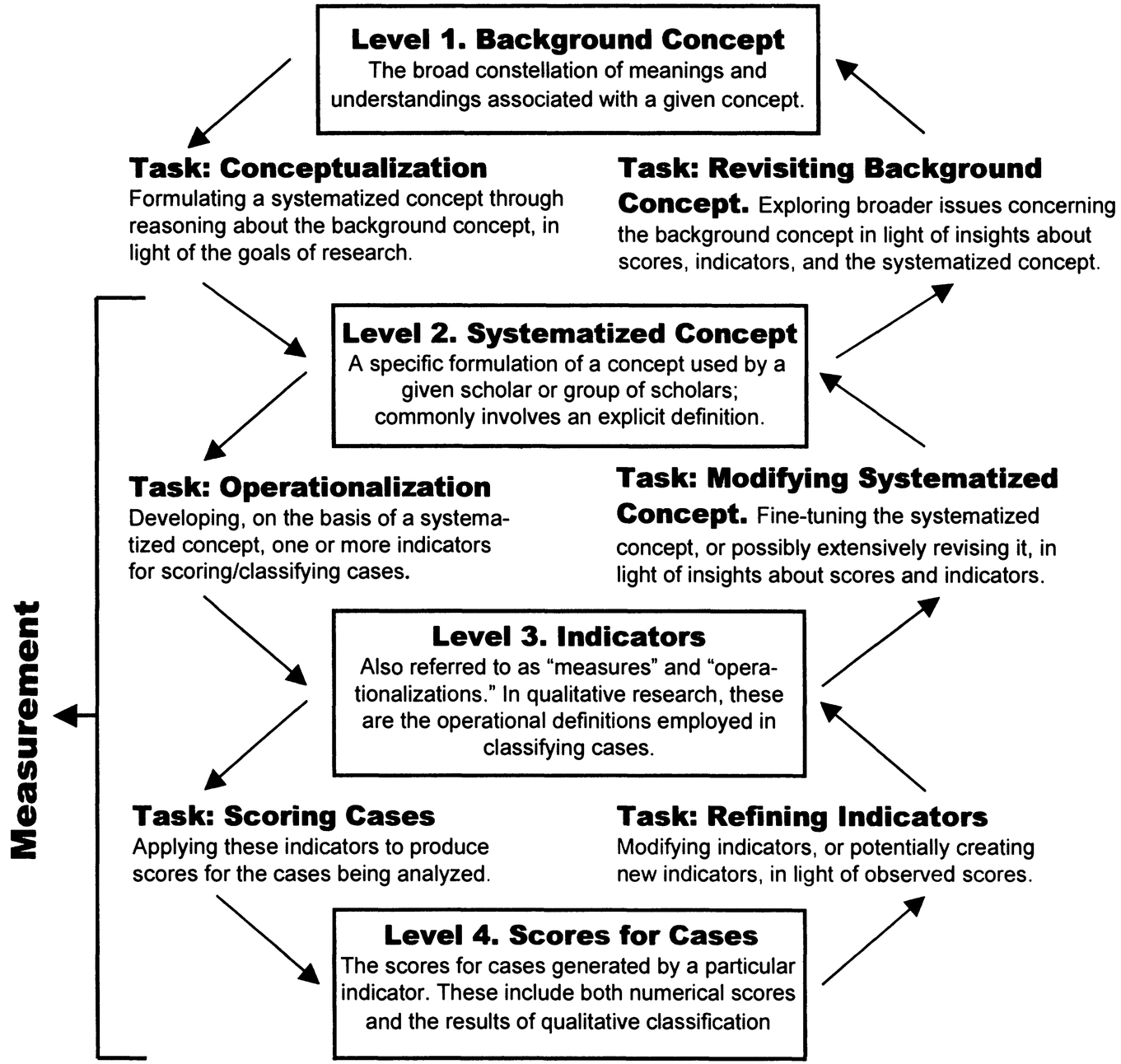


Figure adapted from Kelstedt & Whitten (2018: 10).

2

FIGURE 1. Conceptualization and Measurement: Levels and Tasks



Source: Adcock & Collier (2001: 531).

2

"A **descriptive argument** describes some aspect of the world.

In doing so it aims to answer **<u>what</u> questions** (e.g. when, whom, out of what, in what manner) about a phenomenon or a set of phenomena."

(Gerring 2012: 722, emphasis added)

2

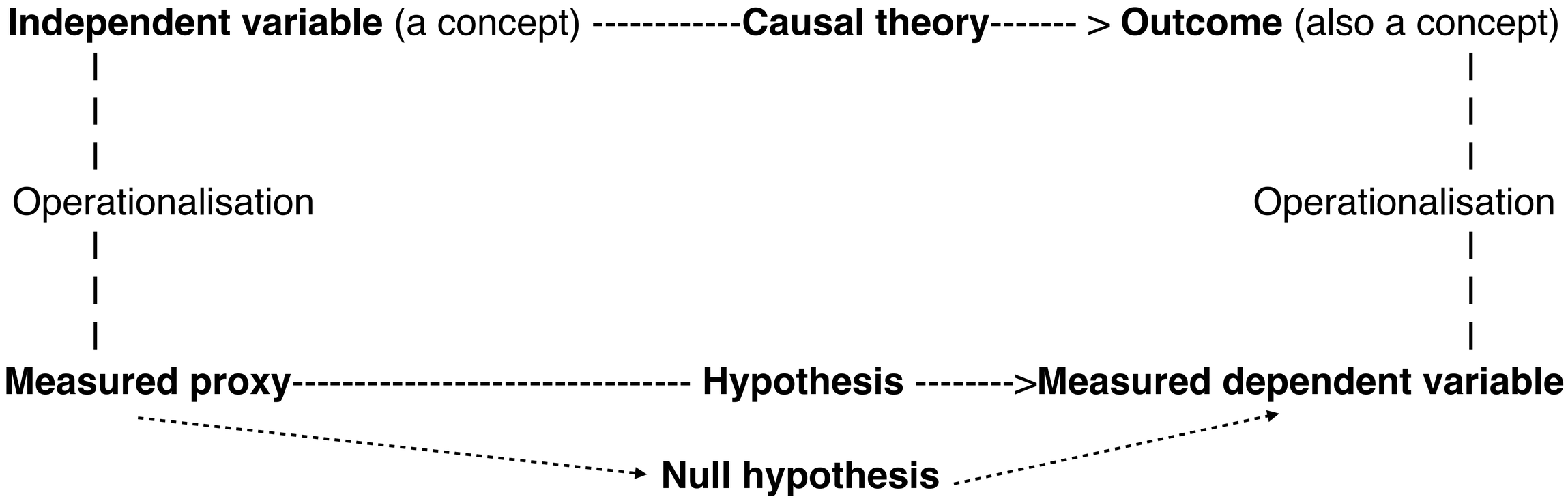


Figure adapted from Kelstedt & Whitten (2018: 10).

2

As Gerring (2012) makes clear, most current political science research focuses on **causal inference** rather than **description**.

However, description and causality are intimately related and can often overlap.

First, we need to understand the ***what*** before we can ask ***why.***

2

scholar.google.com/citations?user=xogVdS0AAAAJ&hl=en&oi=sra

Google Scholar

Cullen S Hendrix

FOLLOW

Professor, Korbel School, University of Denver & Nonresident Senior Fellow, PIIE
Verified email at du.edu - Homepage

political economy environmental politics political science food security international relations

TITLE	CITED BY	YEAR
Measuring state capacity: Theoretical and empirical implications for the study of civil conflict CS Hendrix Journal of Peace Research 47 (3), 273-285	870	2010
Climate change, rainfall, and social conflict in Africa CS Hendrix, I Salehyan Journal of Peace Research 49 (1), 35-50	666	2012
Social conflict in Africa: A new database I Salehyan, CS Hendrix, J Hamner, C Case, C Linebarger, E Stull, ... International Interactions 38 (4), 503-511	497	2012
Trends and triggers: Climate, climate change and civil conflict in Sub-Saharan Africa CS Hendrix, SM Glaser Political Geography 26 (6), 695-715	488	2007
The Social Conflict in Africa Database: New Data and Applications I Salehyan, CS Hendrix, C Case, C Linebarger, E Stull, J Williams Working paper, The University of North Texas	486 *	2010

Research article

Journal of Peace Research
47(3) 273–285

DOI: 10.1177/0022343310361838
jpr.sagepub.com
SAGE

Measuring state capacity: Theoretical and empirical implications for the study of civil conflict

Cullen S Hendrix

Department of Political Science, University of North Texas; and Centre for the Study of Civil War, International Peace Research Institute, Oslo (PRIO)

Abstract

This article identifies and addresses key conceptual and measurement issues raised by measures of state capacity in studies of civil conflict. First, it reviews competing definitions and operationalizations of state capacity, focusing specifically on those that emphasize (1) military capacity, (2) bureaucratic administrative capacity, and (3) the quality and coherence of political institutions. Second, it critically assesses these measures on the basis of construct validity, focusing attention on whether they accurately capture the theoretical concept of state capacity, and whether they allow the researcher to differentiate between competing causal mechanisms. Third, it employs principal factor analysis to identify the underlying dimensionality of 15 different operationalizations of state capacity. State capacity is characterized by low dimensionality, with three factors – or dimensions of state capacity – explaining over 90% of the variance in the 15 measures. While the first factor, *rational legality*, captures bureaucratic and administrative capacity, the second, *rentier-autocraticness*, and third, *neopatrimoniality*, capture aspects of state capacity that cut across theoretical categories. The article concludes by suggesting a multivariate approach to modeling state capacity, and that (1) survey measures of bureaucratic quality, and (2) tax capacity are the most theoretically and empirically justified.

Keywords

civil conflict, construct validity, factor analysis, state capacity

Introduction

State capacity is a quality conspicuous both in its absence and presence but difficult to define. Despite its importance for the study of inter- and intrastate conflict, state capacity remains a concept in search of precise definition and measurement. The various contributions to this special issue, and the works on which they build, may advance our understanding of the causes of civil conflict, but they represent different notions and operationalizations of the concept. The purpose of my contribution is threefold: first, to review the definitions and operationalizations of state capacity in the civil war literature; second, to assess their validity; and third, to determine whether they point to a common quality – or set of qualities – that can inform work relating state capacity to conflict.

Within the civil war literature, interest in state capacity has coincided with a turn away from a debate over motive (whether economic greed or societal grievance) and toward the political opportunity structure that affects potential rebels' decisions to fight. The political opportunity model (Tilly, 1978) places state capacity at the center. The decision to rebel takes into account the government's capacity for repression and accommodation. If the state is capable of repressing, then the likelihood of capture will be higher and rebellion will be less likely. If the state is capable of accommodating grievances via institutionalized channels, such as redistribution, the granting of autonomy rights, or the incorporation of dissident movements within the party system, then the motivation for violent rebellion will be lessened and conflict will be less likely.

In either the repressive or accommodative response scenario, state capacity is central. For a state to repress, it must identify potential rebels and apply coercion. For a state to accommodate, it must redistribute resources and power. Yet these are two very different notions of state capacity. The articles that comprise this special issue use at least seven different definitions and operationalizations of the concept, with another eight playing prominent roles in the literatures on conflict and economic development. It is an open question, however, whether these measures capture distinct theoretical concepts or vectors of variance.

This article addresses three theoretical definitions of state capacity: military power, bureaucratic/administrative capacity, and the quality and coherence of political institutions. Decisions about how to best operationalize the concept of state

Corresponding author:
cullen.hendrix@unt.edu

2

Are political science topics just different?

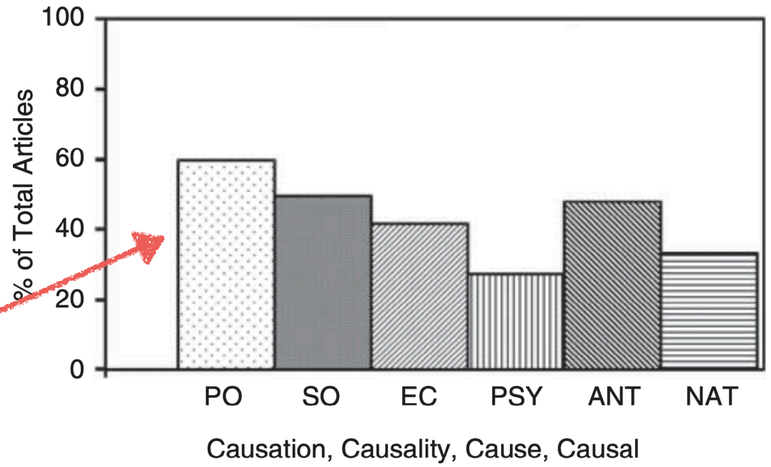


Fig. 4. The disciplines compared, 1980–99
Notes: The share of all articles (not reviews, editorials, or other matter) within top journals in various disciplines mentioning at least one of the following search terms: *causation*, *causality*, or *causal*. The denominator of the ratio – total articles within each stipulated period – was provided by JSTOR's data support team and is available upon request. Searches conducted using the JSTOR on-line search function in November, 2008.

Political Science (PO) journals include: *American Political Science Review*, *American Journal of Political Science*, *and World Politics*. Sociology (SO) journals include: *American Journal of Sociology*, *American Sociological Review*, and *Social Forces*. Economics (EC) journals include: *American Economic Review*, *Quarterly Journal of Economics*, and *Journal of Political Economy*. Psychology (PSY) journals include the *American Journal of Psychology*. (The eight other psychology journals in the JSTOR collection are subfield journals, and thus inappropriate for our purpose.) Anthropology (ANT) journals include: *American Anthropologist*, *American Ethnologist*, and *Journal of the Royal Anthropological Institute/Man*. Natural science (NAT) journals include all journals listed in JSTOR under the following disciplinary categories: Biological Sciences, Botany and Plant Sciences, Developmental and Cell Biology, Ecology and Evolutionary Biology, General Science, Health Sciences, Mathematics, and Zoology (N = 432).

Source: Gerring (2012: 731)

2

Concepts—Economic output, population, democracy

Measurement—GDP, Polity, V-Dem

Why is **falsifying** descriptive arguments so hard?

Describing a concept: What is democracy and how should we measure it?

Causal argument: Does democracy increase the chance of victory in war?

2

"A description of even the smallest slice of reality can **never be exhaustive**."

(Max Weber 1905, quoted in Gerring 2012: 738)

"Any phenomenon of significance to social science is likely to call up **multiple words**, and **multiple definitions** of those words."

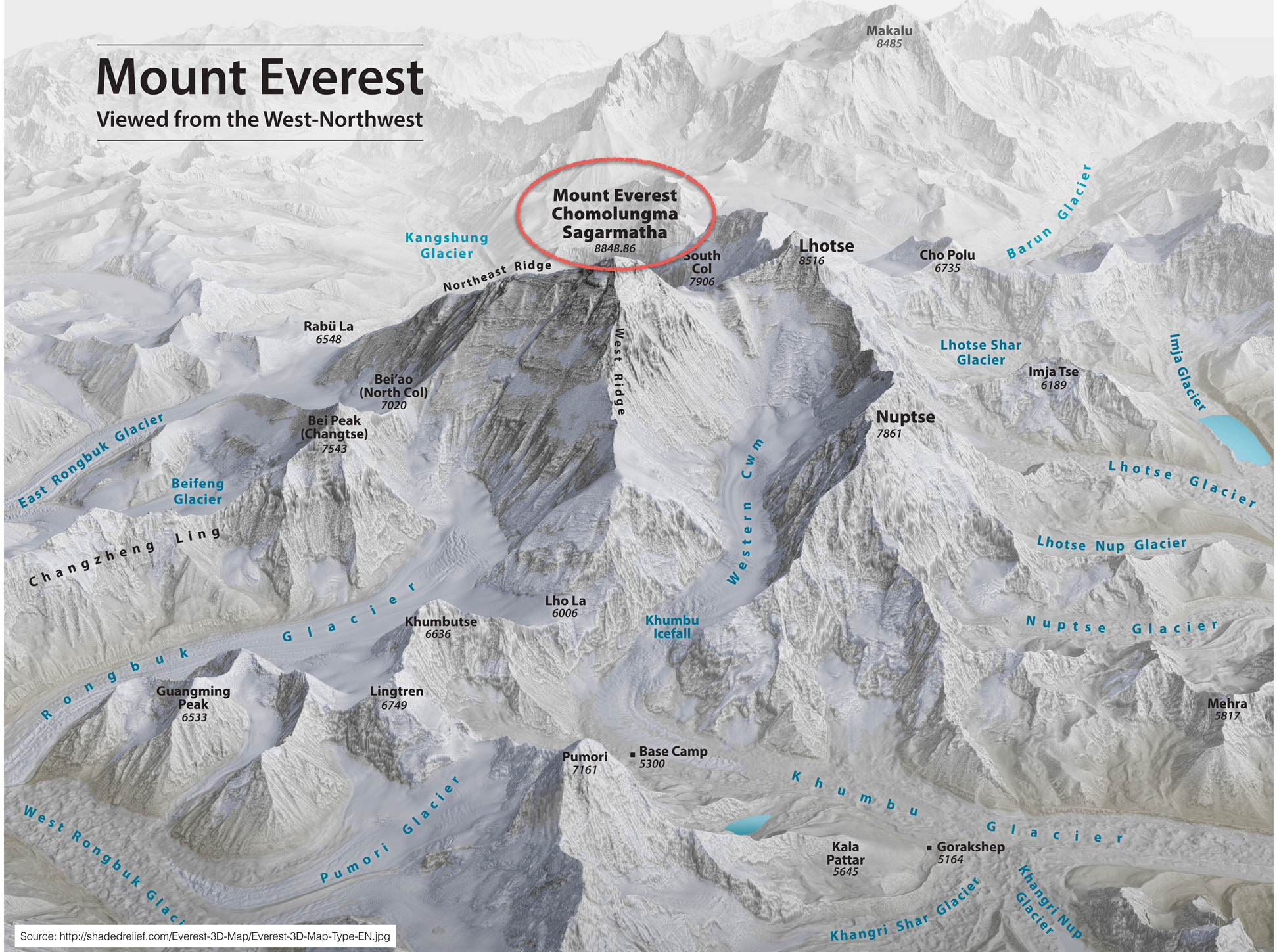
(Gerring 2012: 738).

"To describe something is to **assert its ultimate value**,"

(Gerring 2012: 740)

Therefore, descriptions include an inherent **subjectivity**.

2



Source: http://shadedrelief.com/Everest-3D-Map/Everest-3D-Map-Type-EN.jpg

2

2

Robustness checks!

We will come back to these techniques in a few weeks.

Political Analysis, 11:2(R)

Correlation versus Interchangeability: The Limited Robustness of Empirical Findings on Democracy using Highly Correlated Datasets

Gretchen Casper
Penn State University

Claudiu Tufis
Penn State University

This article shows that highly correlated measures can produce different results. We identify a democratization model from the literature and test it in over 120 countries from 1951-1992. Then, we check whether the results are robust regarding measures of democracy, time periods, and levels of development. The findings show that measures do matter: while some of the findings are robust, most of them are not. This explains, in part, why the debates on democracy have continued rather than been resolved. More importantly, it underscores the need for more careful use of measures and further testing to increase confidence in the findings. Scholars in comparative politics increasingly are drawn to large-N statistical analyses, often using datasets collected by others. As in any field, we show how they must be careful in choosing the most appropriate measures for their study, without assuming that any correlated measure will do.

1 Introduction

Democracy, like representation or power, is a basic concept in political science that is inherently difficult to measure. While different scholars have accepted different tradeoffs between consistency and operationalization when constructing their measures, resulting in a range of different measures of democracy, their measures correlate highly. It would be a reasonable assumption for a researcher to treat the measures interchangeably, selecting one that best fits the time period, number of countries, or particular variables that she was interested in. However, as we show in this article, despite high correlations, the use of these different measures can produce different results

Authors' note: We acknowledge generous advice from Frank Baumgartner, Scott Bennett, David Brown, Suzanna DeBoef, Scott Gates, Barbara Geddes, and Quan Li.

2

How do we measure **latent, unobservable, unmeasurable constructs**?

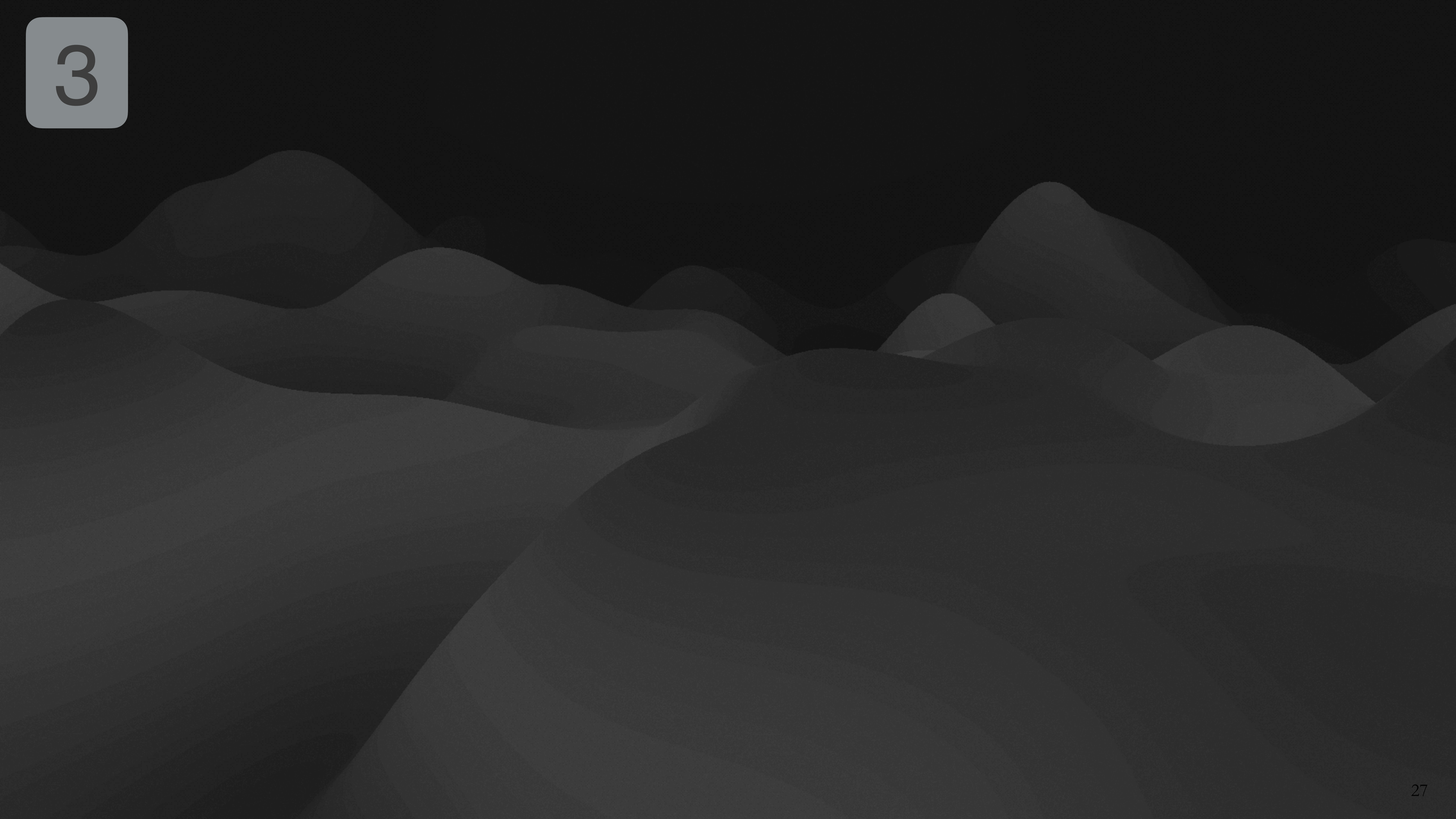
Democracy

Corruption

Conflict

Development

Skill


3

3

Now that we have some ways of describing our topic, let us look at a few ways that we can measure it.

Remember that we should keep in mind **how the data were generated** so as to not try and take away more than we should from the data.

3

Label: Employment status of survey respondent

Values: “employed” or “unemployed”

Variable type:

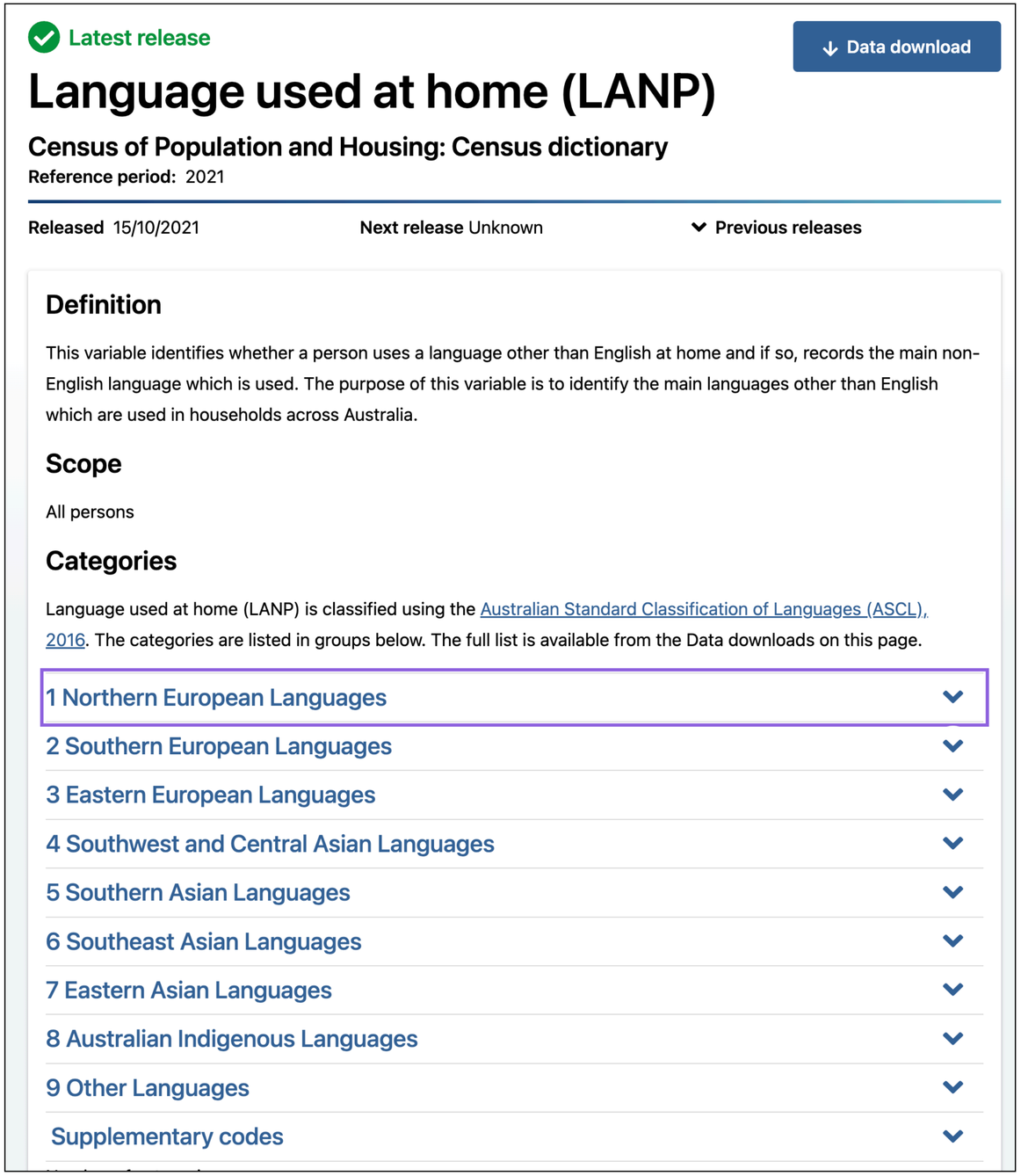
(1) ***categorical/nominal*** [*unemployed, employed*]

(2) **ordinal** [*<5 hours, 5-15 hours, 15-35, >35 hours worked per week*]

(3) **continuous/interval/ratio** [time worked last week]

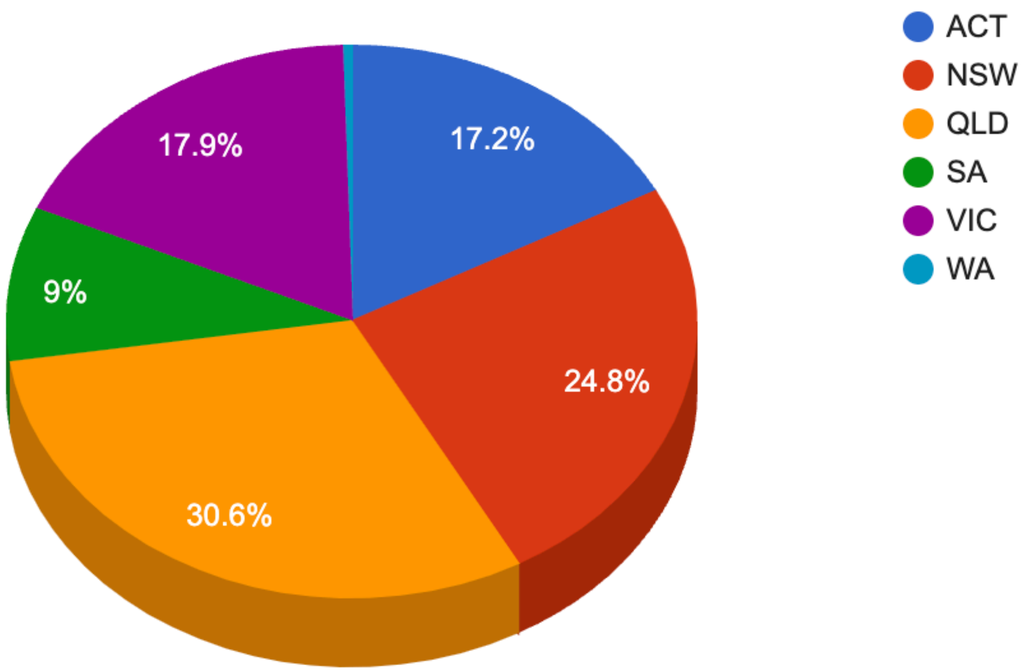
3

We can put cases into categories based on their values, but we cannot **rank** or order them.



3

Magpie swooping attack percentages across Australia by State 2022

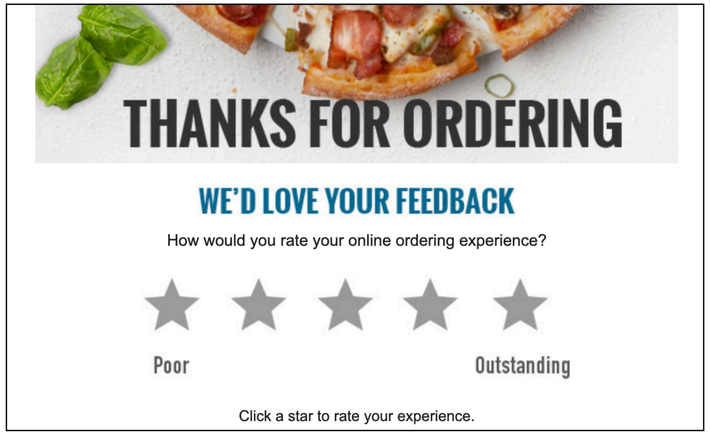


Source: https://www.magpiealert.com/Swooping-Magpie-Attack-Statistics-2022

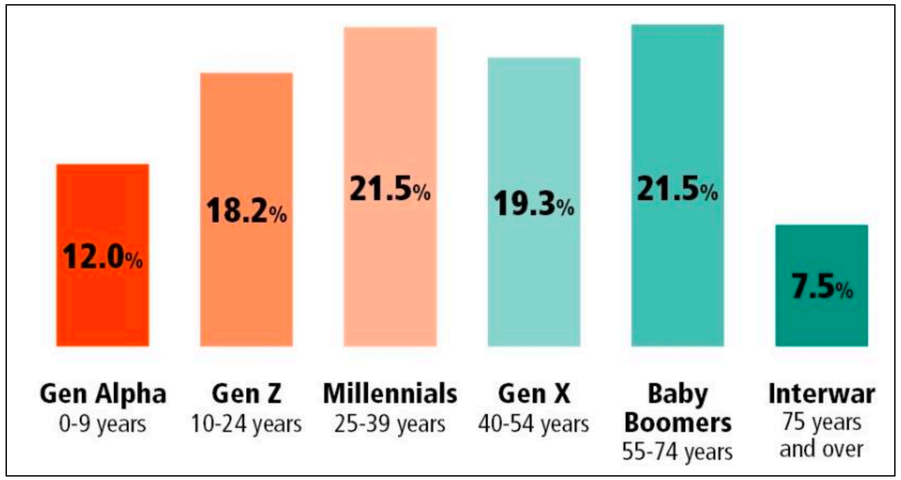
3

Variables for which cases have values where we **can** make universal ranking distinctions.

If we treat an ordinal variable like a categorical variable, we are acting as if we have less information than we really do.



Source: an email I received after recently ordering Dominos.

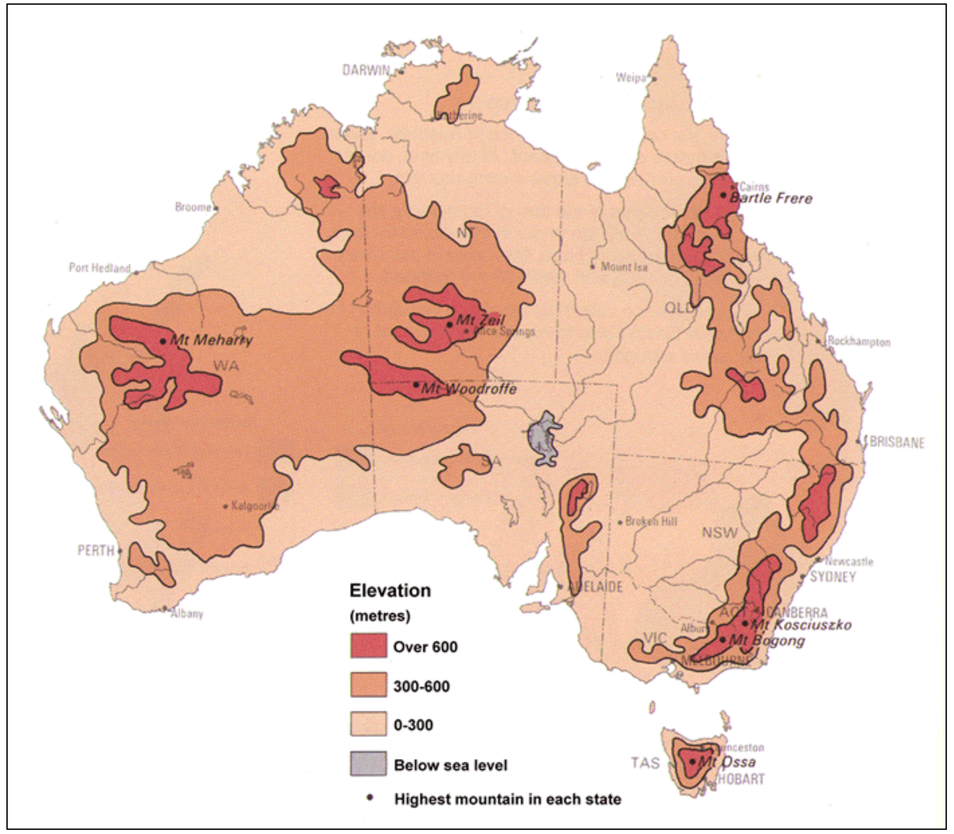


Source: https://www.abs.gov.au/statistics/people/people-and-communities/snapshot-australia/2021

3

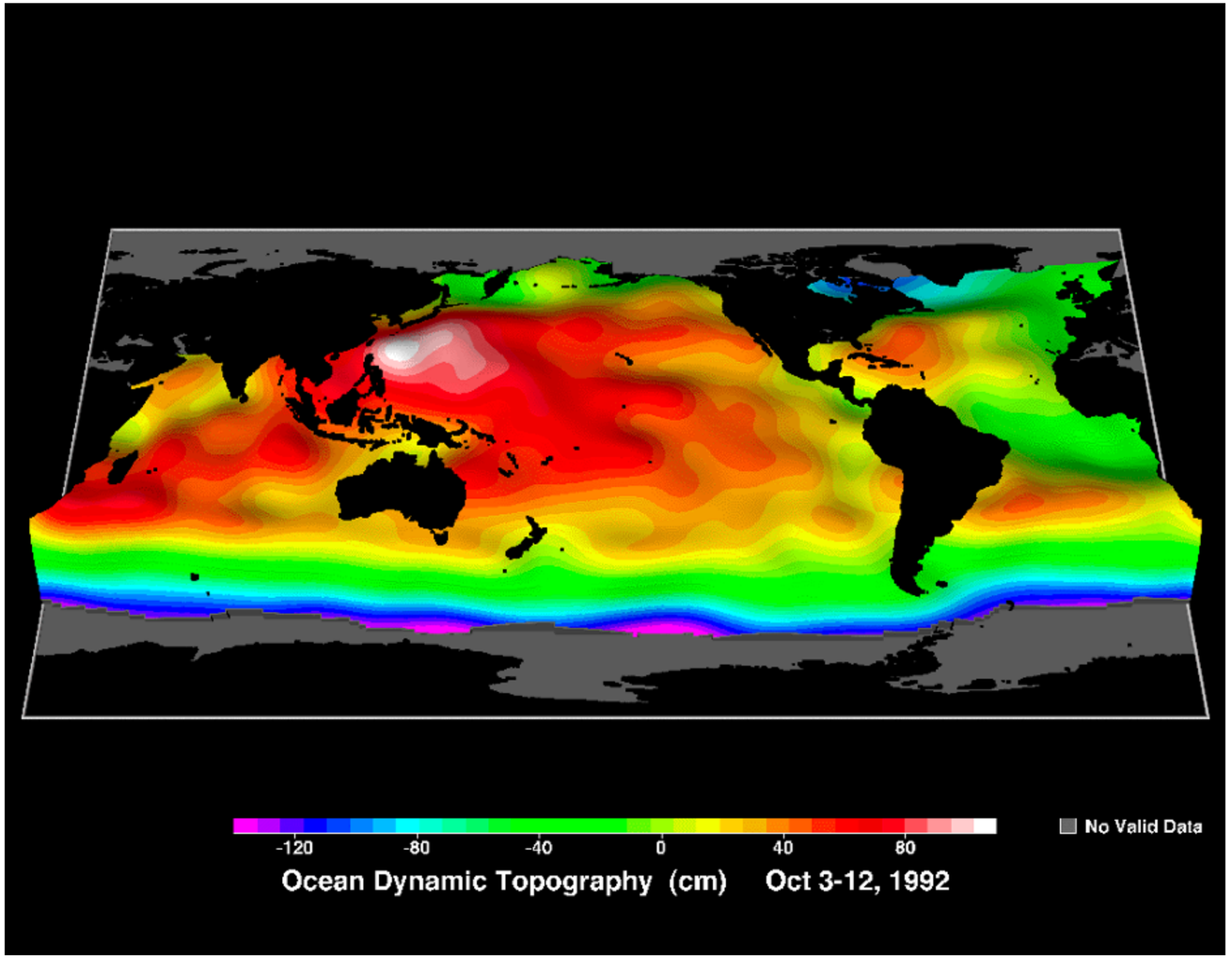
Sometimes called **interval** variables or **ratio** variables (if they have a meaningful 0).

They have **equal unit differences**.

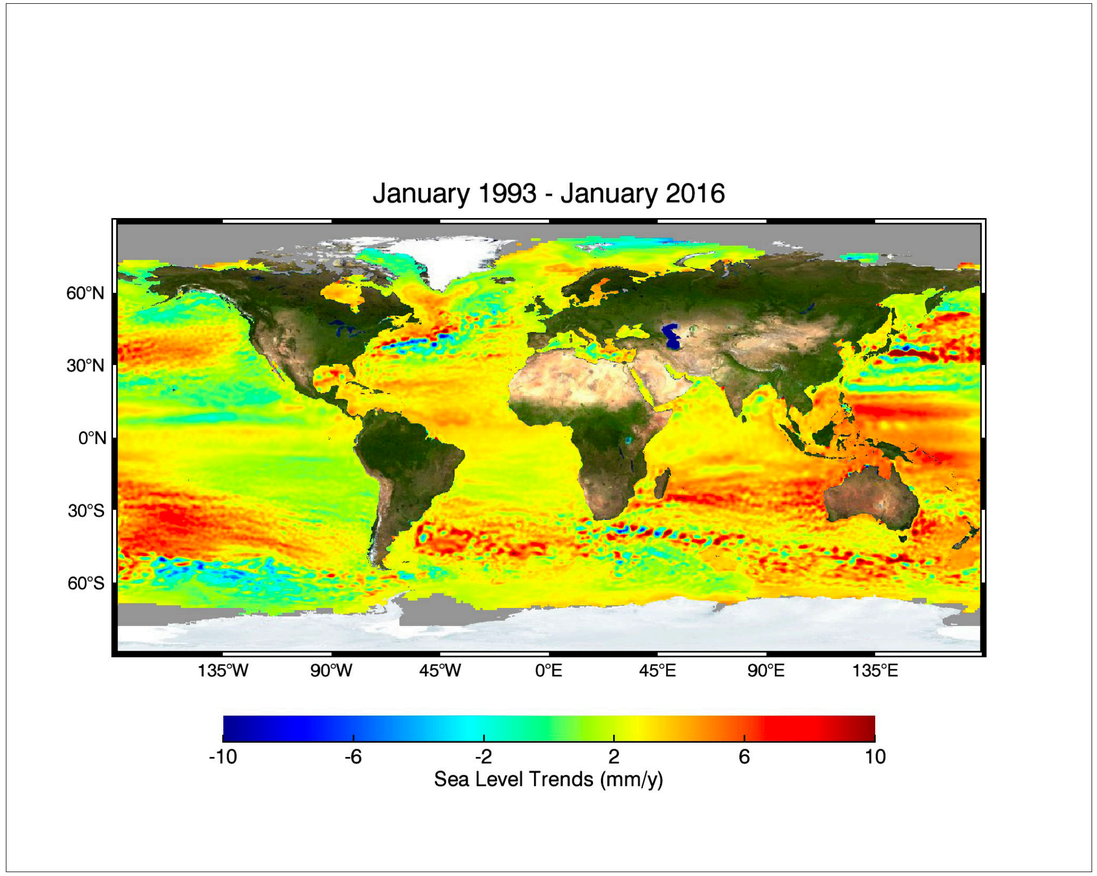


Source: https://www.ga.gov.au/__data/assets/image/0013/12640/GA11759.gif

3



Source: NASA (https://climate.nasa.gov/ask-nasa-climate/2990/sea-level-101-what-determines-the-level-of-the-sea/)



Source: NASA (https://climate.nasa.gov/internal_resources/2143/)

3

Source: https://www.weather-atlas.com/weather/images/city/0/3/2332830-1000-75.jpg

3

Usually, we focus on the **frequency** distribution of categorical variables with a table, pie charts, or bar graphs.

The only central tendency statistic is the **mode** (the most frequent value).

Quantiles (including percentiles) are also used. They are a measure of **position** within a distribution.

3

SAT CollegeBoard

SAT® Understanding Scores

2021

Percentiles for Total Scores

Total Score	Nationally Representative Sample	SAT User
1600	99+	99+
1590	99+	99+
1580	99+	99+
1570	99+	99+
1560	99+	99+
1550	99+	99
1540	99+	99
1530	99+	99
1520	99+	99
1510	99	98
1500	99	98
1490	99	98
1480	99	97
1470	99	97
1460	99	96
1450	99	96
1440	98	95
1430	98	95
1420	98	94
1410	97	94
1400	97	93
1390	97	93
1380	96	92
1370	96	91
1360	95	91
1350	94	90
1340	94	89
1330	93	88
1320	93	87
1310	92	87
1300	91	86
1290	90	85
1280	89	84
1270	88	83
1260	87	82
1250	86	81
1240	85	79
1230	84	78
1220	83	77
1210	82	76
1200	81	74
1190	80	73

Total Score	Nationally Representative Sample	SAT User
1180	78	72
1170	77	70
1160	76	69
1150	74	67
1140	73	66
1130	71	64
1120	70	63
1110	69	61
1100	67	59
1090	65	58
1080	63	56
1070	61	54
1060	60	52
1050	58	51
1040	56	49
1030	54	47
1020	52	45
1010	50	44
1000	48	42
990	46	40
980	44	39
970	42	37
960	40	35
950	38	34
940	36	32
930	35	30
920	33	29
910	31	27
900	29	26
890	27	24
880	26	23
870	24	21
860	23	20
850	21	19
840	20	17
830	18	16
820	17	15
810	16	13
800	14	12
790	13	11
780	11	10
770	10	9

Total Score	Nationally Representative Sample	SAT User
760	9	8
750	8	7
740	7	6
730	6	5
720	5	4
710	4	3
700	4	3
690	3	2
680	2	2
670	2	1
660	1	1
650	1	1
640	1	1
630	1	1
620	1-	1-
610	1-	1-
600	1-	1-
590	1-	1-
580	1-	1-
570	1-	1-
560	1-	1-
550	1-	1-
540	1-	1-
530	1-	1-
520	1-	1-
510	1-	1-
500	1-	1-
490	1-	1-
480	1-	1-
470	1-	1-
460	1-	1-
450	1-	1-
440	1-	1-
430	1-	1-
420	1-	1-
410	1-	1-
400	1-	1-

3

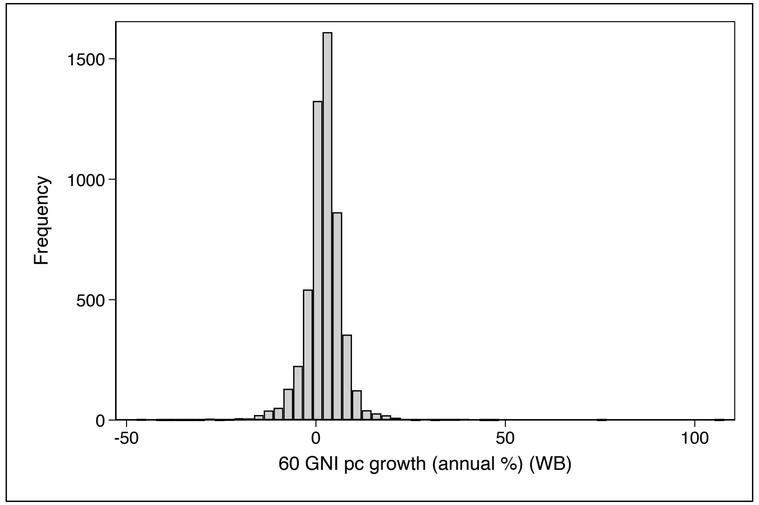
We are primarily interested in the **central tendency** and the **distribution** of values around this central tendency.

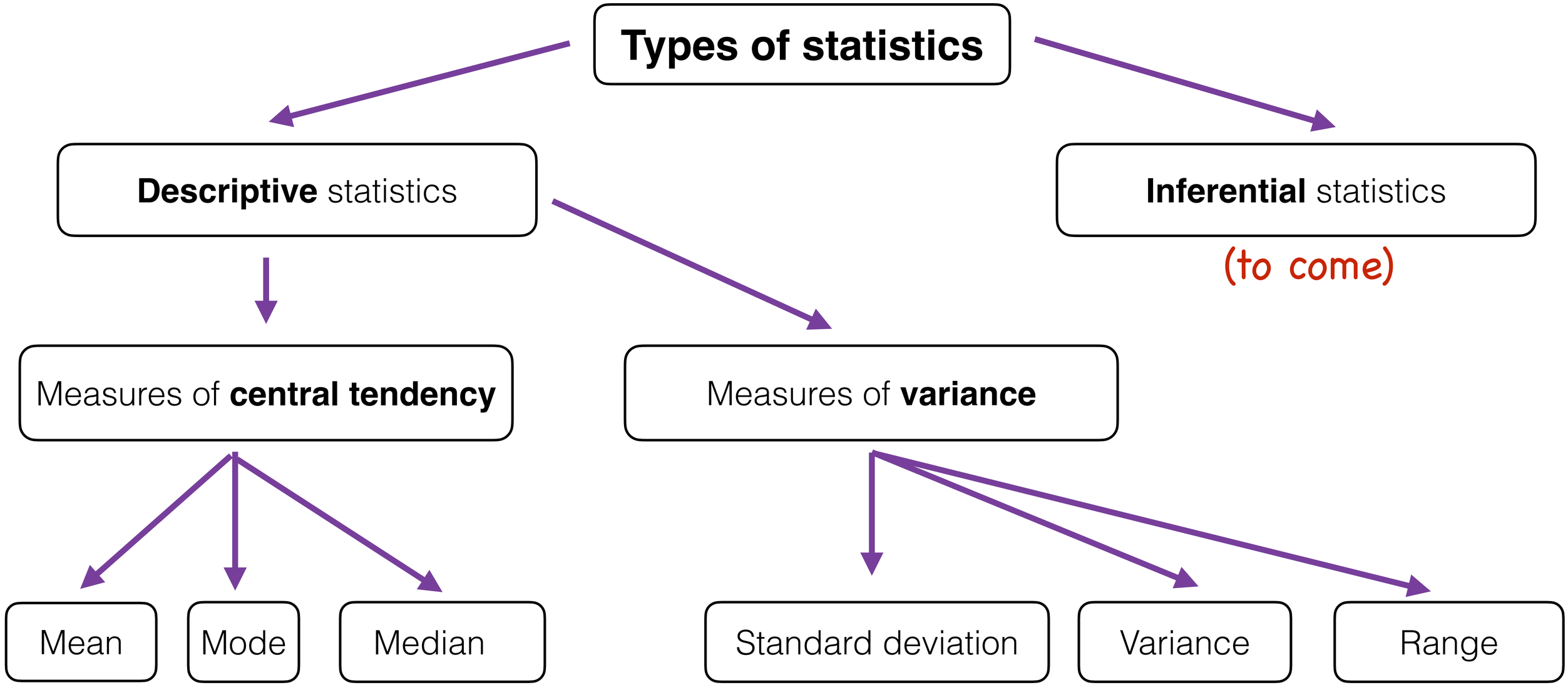
We are also interested in **outliers**.

The midpoint value is the **median.**

The average value is the **mean.**

The dispersion around the mean is described by the **standard deviation**.




Types of statistics
Descriptive statistics
Inferential statistics
(to come)
Measures of central tendency
Measures of variance
Mean
Mode
Median
Standard deviation
Variance
Range

3

Mean = sum of observations / number of observations

Desirable properties are that the **derivations** from the mean are zero-sum and the **least squares** property (to be discussed later).

3

A sample's **standard deviation** (*sd*) is given by $sd = \sqrt{variance(y)}$

Put simply, the average difference between an observation and the mean

Or more concretely:

$$sd = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n - 1}}$$

Where:

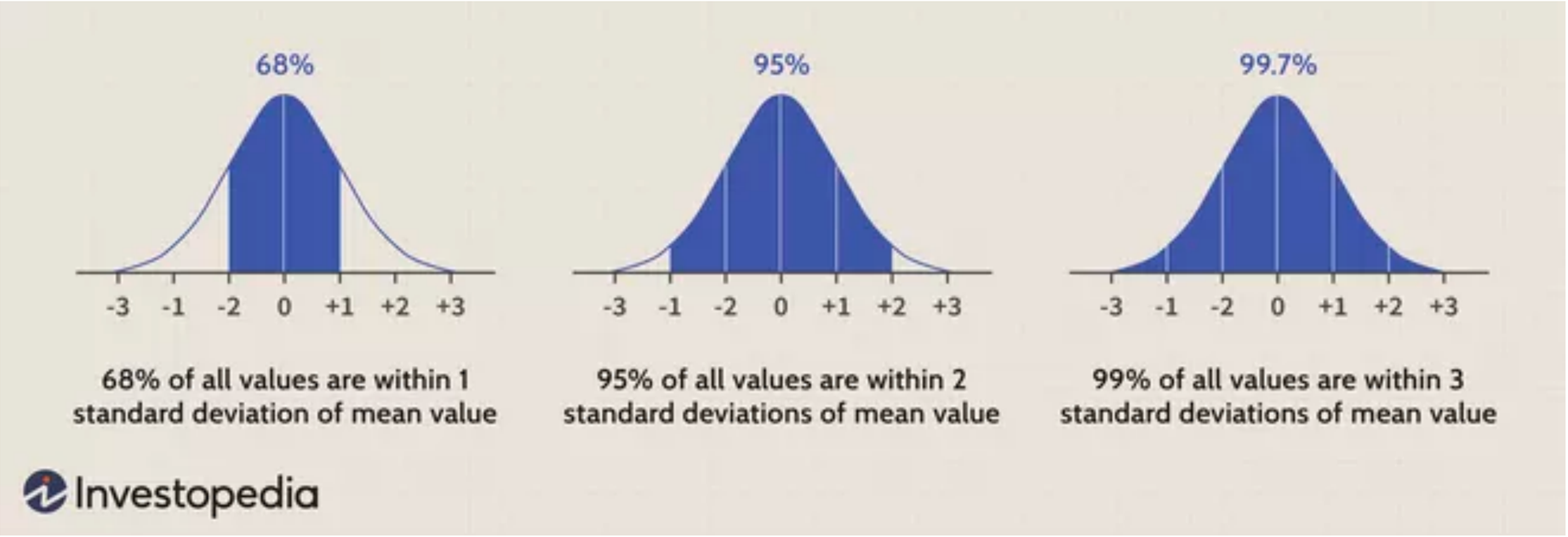
$\bar{x}$ is your variable's mean.

x_i is an individual value.

n is the sample size.

3

With only the mean and standard deviation we can tell a lot about our observations if they approximate the normal distribution.



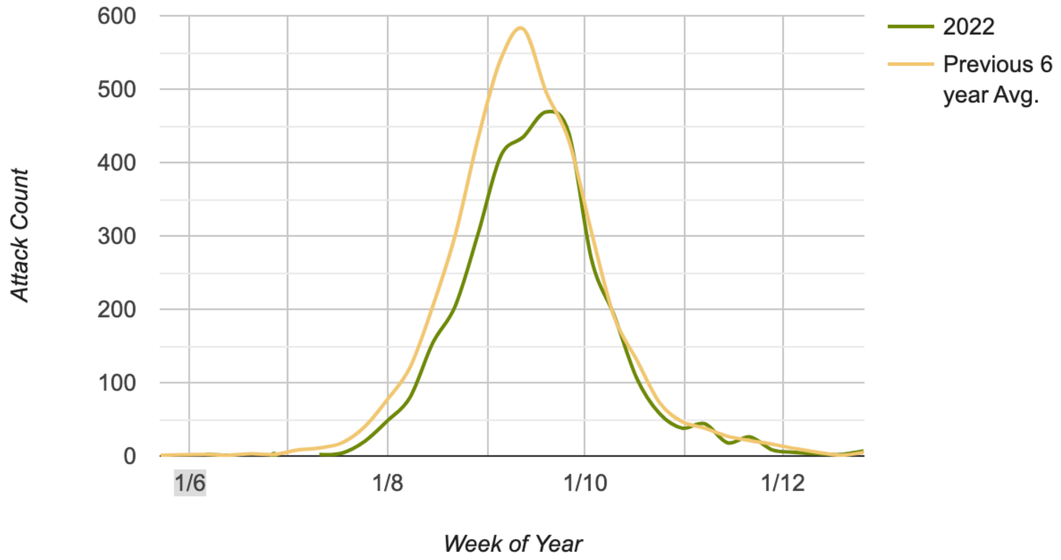
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

Where:
μ= mean
σ =standard deviation

Source: https://www.investopedia.com/terms/n/normaldistribution.asp

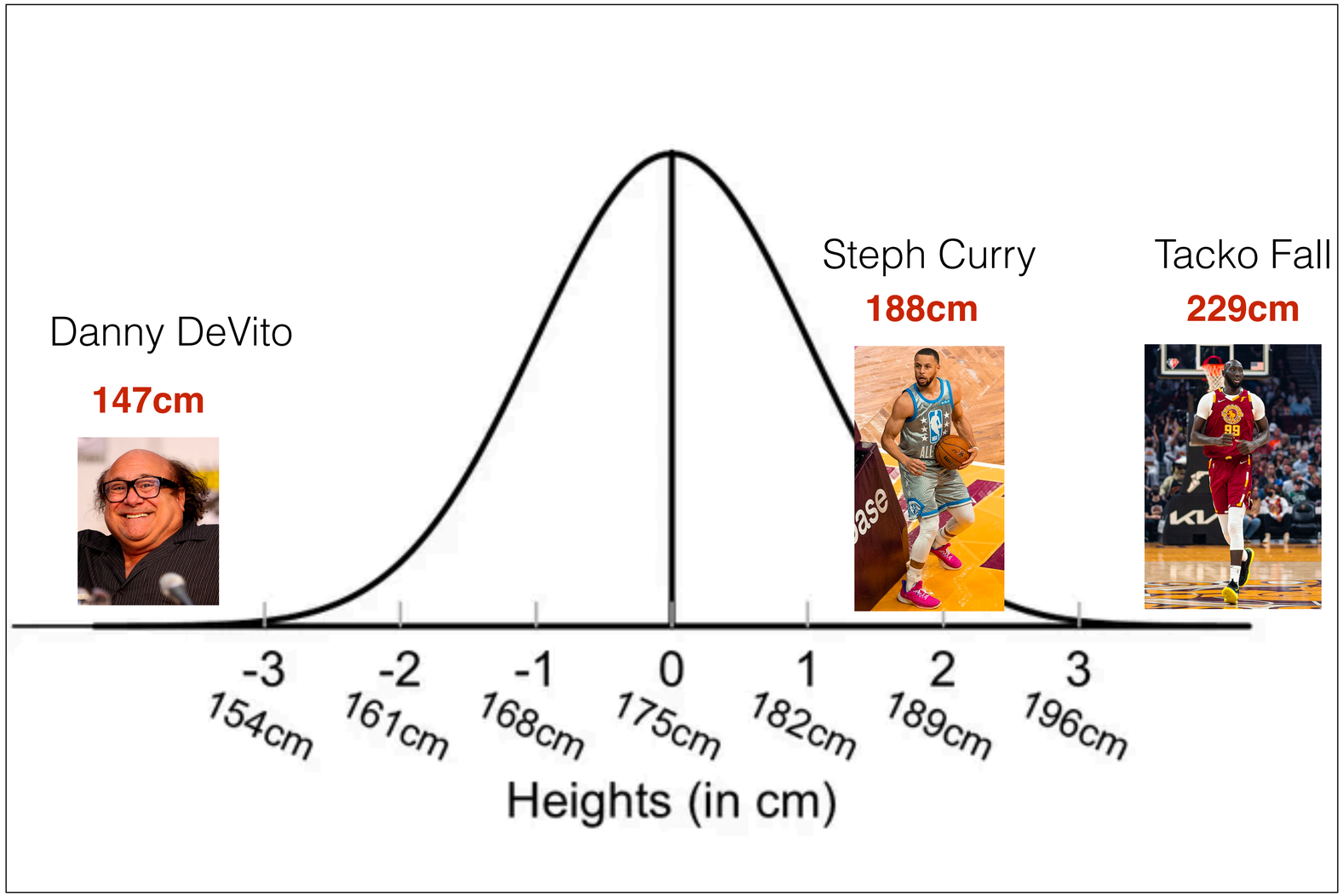
2

Magpie swooping attack counts each week 2022



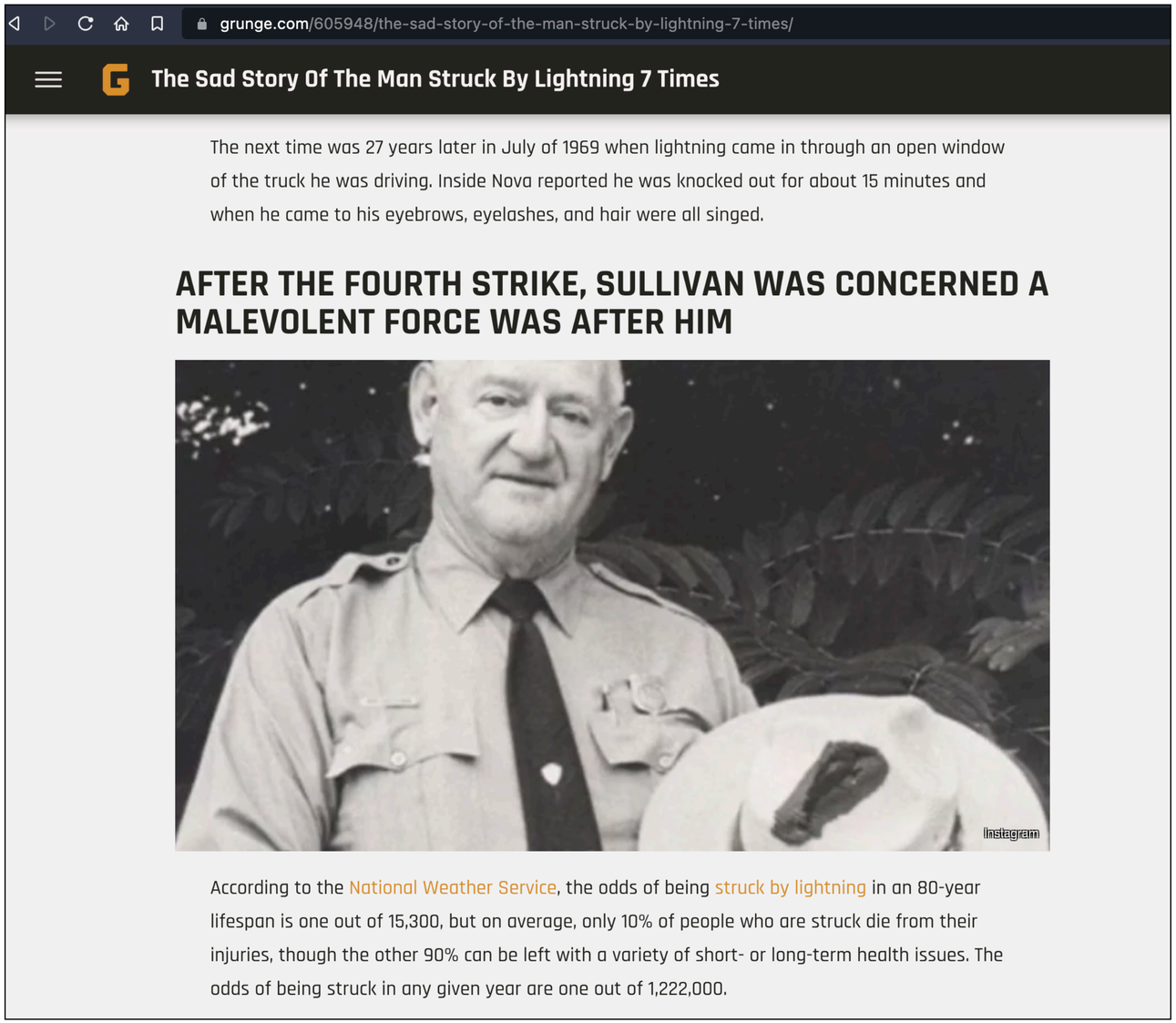
Source: Magpie alert (https://www.magpiealert.com/Swooping-Magpie-Attack-Statistics-2022)

3



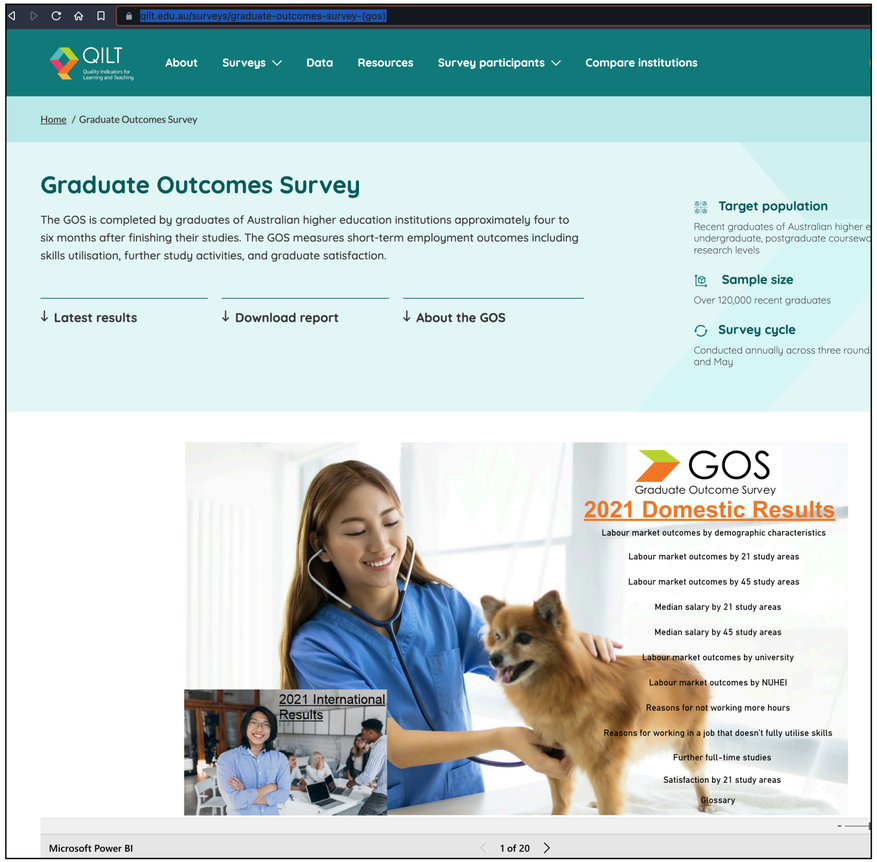
Source: https://www.investopedia.com/terms/n/normaldistribution.asp

3



Source: https://www.grunge.com/605948/the-sad-story-of-the-man-struck-by-lightning-7-times/

3



https://www.qilt.edu.au/surveys/graduate-outcomes-survey-(gos)

3

FIA Formula 1 World Championship™

ROLEX

FORMULA 1 ROLEX BELGIAN GRAND PRIX 2024 - Spa-Francorchamps

Race History Chart

LAP 1	GAP	TIME	LAP 2	GAP	TIME	LAP 3	GAP	TIME	LAP 4	GAP	TIME	LAP 5	GAP	TIME
16		1:51.912	16		1:50.240	44		1:49.109	44		1:49.808	44		1:49.376
44	0.788	1:52.700	44	0.397	1:49.849	16	1.013	1:50.519	16	1.001	1:49.796	16	1.119	1:49.494
11	1.527	1:53.439	11	1.527	1:50.240	11	2.004	1:49.983	11	1.986	1:49.790	11	2.506	1:49.896
81	2.336	1:54.248	81	2.260	1:50.164	81	2.725	1:49.971	81	2.764	1:49.847	81	3.473	1:50.085
63	2.851	1:54.763	63	2.771	1:50.160	63	3.277	1:50.012	63	3.526	1:50.057	63	4.335	1:50.185
55	3.358	1:55.270	55	3.378	1:50.260	55	3.985	1:50.113	55	4.059	1:49.882	55	4.920	1:50.237
4	3.815	1:55.727	4	4.079	1:50.504	4	4.704	1:50.131	4	4.908	1:50.012	4	5.687	1:50.155
14	4.665	1:56.577	1	4.859	1:49.828	1	5.494	1:50.141	1	5.741	1:50.055	1	6.503	1:50.138
1	5.271	1:57.183	14	5.741	1:51.316	14	6.439	1:50.204	14	7.052	1:50.421	14	8.366	1:50.690
23	5.409	1:57.321	23	6.452	1:51.283	23	7.146	1:50.200	23	7.648	1:50.310	23	8.995	1:50.723
31	5.935	1:57.847	31	7.007	1:51.312	31	8.019	1:50.518	31	8.582	1:50.371	31	9.842	1:50.636
10	6.642	1:58.554	10	7.675	1:51.273	10	8.926	1:50.757	10	9.484	1:50.366	10	10.636	1:50.528
77	6.849	1:58.761	77	8.061	1:51.452	77	9.640	1:51.085	77	10.359	1:50.527	77	11.445	1:50.462
3	7.344	1:59.256	3	8.645	1:51.541	3	10.354	1:51.215	3	11.261	1:50.715	3	12.199	1:50.314
18	7.706	1:59.618	18	9.120	1:51.654	18	11.008	1:51.394	18	12.019	1:50.819	18	13.138	1:50.495
27	8.244	2:00.156	27	9.804	1:51.800	27	11.532	1:51.234	27	12.636	1:50.912	27	14.029	1:50.769
20	8.836	2:00.748	20	10.328	1:51.732	20	12.136	1:51.314	20	13.332	1:51.004	20	14.743	1:50.787
24	9.209	2:01.121	24	11.068	1:52.099	22	13.425	1:51.051	22	14.475	1:50.858	22	16.055	1:50.956
22	9.729	2:01.641	22	11.880	1:52.391	2	14.186	1:51.366	2	15.150	1:50.772	2	16.889	1:51.115
2	10.278	2:02.190	2	12.326	1:52.288	24	82.684	3:01.122	24	85.252	1:52.376			

3

What can **descriptive inference** tell us that causal inference cannot?

What are the basic **descriptive statistics**?

3

Political scientists spend much more time thinking about **causal inference** and **data** analysis than they think about **conceptualising** and **describing** their causes (X's) and outcomes (Y's).

However, the former is of limited utility without the latter.

Image source: https://imgflip.com/memetemplate/57007095/Wrong-tool-for-the-job

3