Ecological performance of detecting data fabrication

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Any field of empirical inquiry is faced with cases of scientific misconduct at some point, either in the form of fabrication, falsification or plagiarism (FFP). Psychology was faced with Stapel; medical sciences were faced with Poldermans and Macchiarini; life sciences were faced with Voignet. These are just a few examples of misconduct cases in the last decade. Overall, an estimated 2% of all scholars have admitted to falsifying or fabricating research results at least once (Fanelli, 2009) and this is likely to be an underestimate due to socially desirable responses. The detection rate of data fabrication is likely to be even lower; for example, only around a dozen cases are discovered in the United States and the Netherlands, despite covering several hundreds of thousands of researchers. At best, this amounts to a detection rate far below 1% of those 2% who admit to fabricating data — the tip of a seemingly much larger iceberg.

In order to stifle attempts at data fabrication, improved detection of fabricated data is considered to deter such harmful attempts. Although deterrence theory dates back to the middle of the 17th century (Hobbes, 1651), its implementation has not occurred equally across fabrication, falsification, and plagiarism. Basically, deterrence theory stipulates that with increased risk of detection, the utility of scientific misconduct (for this context) will decrease and therefore fewer people will engage in such behaviors. This principle of deterrence has been implemented with plagiarism scanners, a development that already started a long time ago (e.g., A. Parker & Hamblen, 1989). In the last decade, detecting image manipulation has become one of the few forms of detecting data fabrication . The Journal of Cell Biology and EMBO scan each submitted image for potential manipulation (**???**; The Journal of Cell Biology, 2015), which greatly increases the risk of detecting (blatant) image manipulation. More recently, algorithms have been developed to automate the scanning of images for (subtle) manipulations (Koppers, Wormer, & Ickstadt, 2016). These developments in detecting image manipulation have increased detection risk during the pre-publication and post-publication phase by improving detection mechanisms and increasing the understanding of how images might be manipulated. Moreover, their application also helps researchers systematically evaluate research articles to estimate the extent of the problem of image manipulation (4% of all papers are estimated to contain manipulated images, Bik, Casadevall, & Fang, 2016).

Statistical methods provide one way to improve detection of data fabrication in empirical research. Humans are notoriously bad at understanding and estimating probabilities (Amos Tversky & Kahneman, 1971; e.g., A. Tversky & Kahneman, 1974), which could manifest itself in the fundamentally probabilistic data they try to

fabricate. When data are fabricated, probabilistic principles are easily violated if forgotten at the univariate level, bivariate level, trivatiate level, or beyond (Haldane, 1948). Based on this idea, statistical methods that investigate whether the reported data are feasible under the theoretically probabilistic processes can be used to detect potential data fabrication.

The application of such statistical methods to detect data fabrication has occurred in several cases of scientific misconduct in recent years and has potential for future application beyond these specific cases. For example, problems in papers by Fuji were highlighted with statistical methods (Carlisle, 2012; Carlisle, Dexter, Pandit, Shafer, & Yentis, 2015), resulting in 183 retractions (Oransky, 2015). This method works as follows: in true randomized clinical trials (RCTs), baseline measurements should be statistically equal across groups. As such, the p-values for group comparisons would be expected to be uniformly distributed because the null hypothesis of equal groups is true by definition of the design. In the Fuji papers, group comparisons showed excessive consistency, resulting primarily in high p-values (e.g., .99, .95) and a high mean p-value across the comparisons, where a mean p-value of .5 is expected. As an illustration, see Table 1, which depicts the assignment of participants to the experimental or control condition for a true randomized design (Set 1) or for a fabricated design (Set 2). The mean p-value for the true randomized design Set 1 is 0.583, whereas the fabricated Set 2 has mean p-value 0.937. Other statistical methods to detect data fabrication are addressed in the theoretical framework. .

Table 1: Examples of participant counts for genuine- and fabricated randomized clinical trials. Set 1 (S1) is randomly generated data under the null hypothesis of random assignment (assumed to be the genuine process), whereas Set 2 (S2) is generated under excessive consistency with equal groups. Each trial contains 100 participants. The p-values

Study	Experimental [S1]	Control [S1]	P-value [S1]	Experimental [S2]	Control [S2]	P-value [S2]
Study 1	45	55	0.317	49	51	0.841
Study 2	52	48	0.689	50	50	1.000
Study 3	52	48	0.689	50	50	1.000
Study 4	48	52	0.689	50	50	1.000
Study 5	60	40	0.046	51	49	0.841
Study 6	61	39	0.028	50	50	1.000
Study 7	49	51	0.841	49	51	0.841
Study 8	52	48	0.689	49	51	0.841
Study 9	50	50	1.000	50	50	1.000
Study 10	49	51	0.841	50	50	1.000

Such statistical methods to detect data anomalies, although developed to quantify suspicions in a specific paper, could be applied to screen multiple papers. The application of such methods can be (semi-)automated if data are available in a machine-readable format that one of the statistical methods can be applied to. An example of such a potential case for mass application of using statistics to detect (potential) data fabrication is in the ClinicalTrials.gov database, where baseline measures across randomized groups are readily available for download and subsequent analysis (C. Hartgerink & George, 2015).

Nonetheless, prior to applying statistical methods to flag potentially problematic results, investigating whether such methods function well enough in detecting problems is required for responsible application. We hardly know how researchers might go about fabricating data. Cases such as Stapel, Fuji, Smeesters, and Sanna provide some insights, but are highly pre-selected (i.e., those who got caught/confessed) and as such, systematically biased. Relatively extensive descriptions in rare and partial autobiographical accounts provide little insight into the actual data fabrication process, except for the setting where it might take place (e.g., late at night when no one is around; Stapel, 2014). However, trustworthiness of these accounts can be called into question. Additionally, the performance of methods to detect data fabrication is highly dependent on the unknown prevalence of data fabrication and the power to actually to detect data fabrication. Given that

we do not know how researchers might fabricate data, the diagnosticity of these methods cannot realistically be assessed.

Throughout this paper, we inspect statistical methods to detect potential data fabrication that can be applied to (1) summary results or (2) raw data. Even though structure and contents of data can look different depending on the structure of a study and the measures, there are certain common characteristics of empirical results and the underlying raw data that can be inspected. For example, summary results frequently include means, standard deviations, test-statistics, and p-values. Raw data frequently contain at least some variables measured at a interval- or ratio scale (Stevens, 1946). Such common characteristics allow for the development of generic statistical methods that can be applied across a varied set of results to screen for problematic data. We review the theoretical framework of the specific methods we apply throughout this paper, but these are not exhaustive of all methods available to test for potential problems in empirical data (Anaya, 2016; Brown & Heathers, 2016; see also Buyse et al., 1999; James Heathers, 2017).

Theoretical framework

In the current paper, we differentiate between statistical methods to detect potential data fabrication based on reported data (i.e., summary results) or raw data. For summary results, we review p-value analysis, variance analysis, and effect size analysis as potential ways to detect data anomalies. P-value analysis can be applied whenever sufficient nonsignificant p-values are reported; variance analysis can be applied whenever a set of variances are reported for independent groups alongside the sample sizes per group; effect size analysis can be used whenever the effect size can be computed [e.g., an APA reported t- or \protect\T1\textdollarF\protect\T1\textdollar-statistic;@10.1525/collabra.71]. For raw data, we review digit analyses (i.e., the Newcomb-Benford law and terminal digit analysis), and multivariate associations as potential ways to detect data anomalies. Digit analyses can be applied when ratio scale measures are present in the raw data; multivariate associations can be applied whenever there is a multivariate relation in the raw data that can be computed and control data is available from the literature.

Detecting data fabrication in summary results

P-value analysis

The distribution of a p-value is uniform if the null hypothesis is true and right-skewed if the alternative hypothesis is true (Fisher, 1925). One p-value is the result of the population effect size, the precision of the estimate, and the observed effect size, whose properties carry over to a set of p-values if those p-values are independent. As such, the p-value distribution of a set of p-values is uniform when the null hypothesis is true, or right-skewed when the alternative hypothesis is true.

When the p-value distribution is not uniform nor right-skewed, it can indicate potential data anomalies. For example, a distribution might show a bump when excessive p-hacking occurs that seeks barely significant results (e.g., Figure 1 in C. H. Hartgerink, Aert, Nuijten, Wicherts, & Assen, 2016). However, data fabricators might create other non-uniform or non-right-skewed distributions, failing to take into account the theoretical boundary conditions. For example, given the frequent misinterpretation of p-values (S. N. Goodman, 1999; Hoekstra, Finch, Kiers, & Johnson, 2006; Sijtsma, 2015), it is possible that the same underlying misinterpration will manifest itself in fabricated data. More specifically, given the frequent misinterpretation of p-valuesas the probability of an effect (D. G. Altman & Bland, 1995; S. Goodman, 2008), researchers who fabricate nonsignificant data might forget to fabricate a uniform p-value distribution and generate only large p-values when fabricating nonsignificant results.

In order to test whether observed p-values are anomalous, we proposed an adaptation of Fisher's method (S. P. O'Brien et al., 2016). This adaptation is a simple reversal of the original Fisher method (Fisher, 1925),

which was introduced as a meta-analytic test for the presence of an effect. This test is computed as

$$\chi^2_{2k} = -2\sum_{i=1}^{k} \ln(p_i)$$

where it tests for right-skew (i.e., more smaller p-values than larger p-values) across the k number of p-values. Reversing the Fisher method results in

$$\chi^2_{2k} = -2\sum_{i=1}^{k} \ln(1 - \frac{p_i - t}{1 - t})$$

where it now tests for left-skew (i.e., more larger p-values than smaller p-values) across the k number of p-values that falls above the threshold t. This threshold is added and can be set to any value between zero and one. Upon writing this paper, it became clear to us that this is reversed Fisher method is similar to the operating principle of Carlisle's method testing for excessive homogeneity across baseline measurements in RCTs (Carlisle, 2012, 2017; Carlisle et al., 2015).

Despite this test being useful for detecting data anomalies in nonsignificant p-values, one exception should be taken into account: wrongly specified one-tailed tests. For properly specified one-tailed tests, the p-value distribution is right-skewed. When wrongly specified, this distribution is reversed and becomes left-skew. As such, any data anomalies detected with this method would need to be inspected for misspecified one-tailed hypotheses to preclude false conclusions.

Variance analysis

Variance- or standard deviation estimates are typically reported to indicate dispersion, but just like the mean there should be sampling error in this estimate proportional to the sample size [i.e., $\sigma/\sqrt{2n}$ under the assumption of normality, p. 351;@yule1922]. A variance estimate follows a χ^2-distribution, which is dependent on the sample size (p. 445; Hogg & Tanis, 2001); that is

$$z_j^2 \sim \left(\frac{\chi^2_{N_j-1}}{N_j - 1}\right) / MS_w$$

where N_j is the sample size of the jth group and MS_w is the normalizing constant resulting in a standardized variance z_j^2. The normalizing constant MS_w is computed as

$$MS_w = \frac{\sum_{j=1}^{k} (N_j - 1)s_j^2}{\sum_{j=1}^{k} (N_j - 1)}$$

where s_j^2 is the variance in the jth group.

The observed dispersion of the variances can be compared to various measures of expected dispersion in the variances. Dispersion can be operationalized in various ways, such as the standard deviation of the variances [denoted in this paper as \protect\T1\textdollarSD_z\protect\T1\textdollar;@10.1177/0956797613480366] or as the range of the variances (denoted as $max - min_z$). Too consistent results would indicate potential anomalies in the reported data. For example, in the Smeesters case three independent conditions from the same study ($n_k = 15$) were reported to have standard deviations 25.09, 24.58, and 25.65. The standard deviation of the standard deviations here is 0.54 (i.e., SD_z). Such consistency (or more consistency) would only be observed in 1.23% of 100,000 simulated replications (Simonsohn, 2013).

Effect size analysis

From our own experience, and anecdotal evidence elsewhere (Bailey, 1991), large effects have previously raised initial suspicions. Taking the observed effect size and transforming it into a correlation, allows for an easy way to assess how extreme the presented result is. One minus the observed correlation can be used as a measure for extreme effects (i.e., $1 - r$); as a heuristic, it can be regarded as a p-value. That is, this measure too ranges from zero to one and the more extreme the effect size, the smaller the value. This method specifically looks at situations where fabricators would want to fabricate the existence of an effect (not the absence of one).

Detecting data fabrication in raw data

Digit analysis

Raw data with ratio- or interval measures can be subjected to digit analysis under specific conditions. More specifically, the properties of the leading (first) digit (e.g., the 1 in 123.45) or the terminal (last) digit (e.g., the 5 in 123.45) can be examined. By analyzing these leading- and terminal digits for deviations from specific digit distributions, it might be possible to screen for problematic data. In this article we focus on leading digit analysis (i.e., Newcomb-Benford Law) and terminal digit analysis to detect potentially problematic data.

Newcomb-Benford law

The Newcomb-Benford law (Benford, 1938; NBL; Newcomb, 1881) states that leading digits do not have an equal probability of occuring under certain conditions. A leading digit is the left-most digit of a numeric value, where a digit is any of the nine natural numbers $(1, 2, 3, ..., 9)$. The distribution of the leading digit, according to the NBL is

$$P(d) = log_{10}\frac{1+d}{d}$$

where d is the natural number of the leading digit and $P(d)$ is the probability of d occurring. Table 2 indicates the expected leading digit distribution based on the NBL. This expected distribution is typically compared to the observed distribution with a χ^2-test ($df = 9 - 1$), which requires a minimum of 45 observations based on the rule of thumb outlined by Agresti (2003) ($n = I \times J \times 5$, with I rows and J columns). The NBL has been applied to detect financial fraud (e.g., Cho & Gaines, 2007), voting fraud (e.g., Durtschi, Hillison, & Pacini, 2004), and also to detect problems in scientific data (e.g., **???**).

Table 2: The expected first digit distribution, based on the Newcomb-Benford Law.

Digit	Proportion
1	0.301
2	0.176
3	0.125
4	0.097
5	0.079
6	0.067
7	0.058
8	0.051
9	0.046

However, given that the NBL only applies under specific conditions that are rarely fulfilled in the social sciences, its applicability for detecting data anomalies in science can be questioned. First, the NBL only applies for true ratio scale measures (**???**; Hill, 1995). Second, sufficient range on the measure is required for

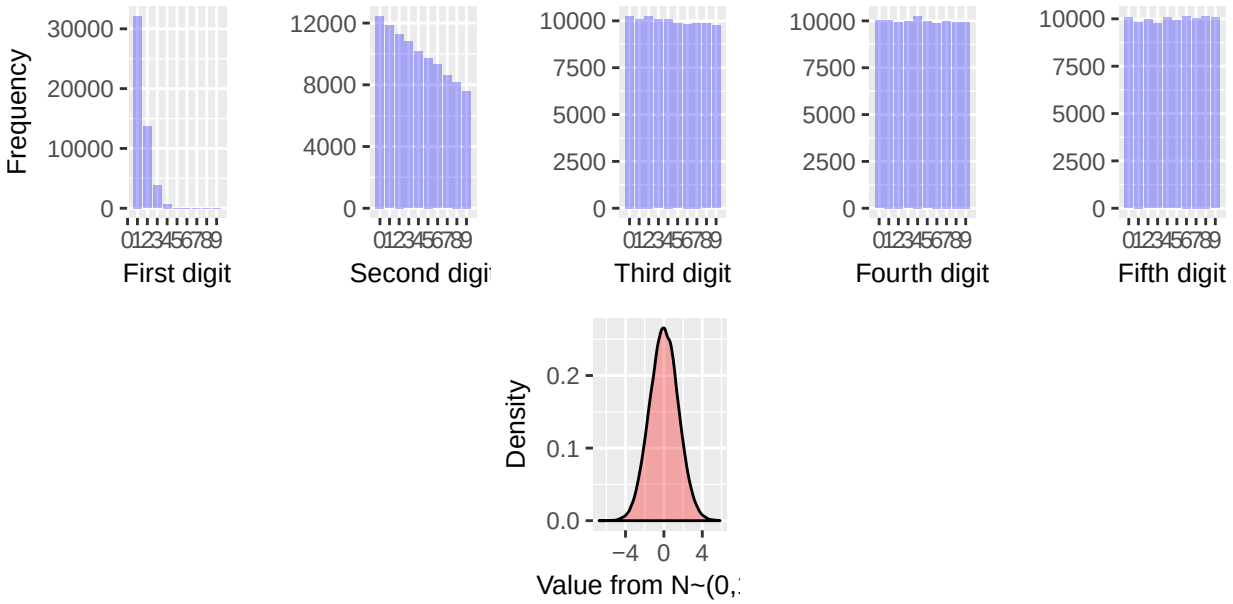


Figure 1: Illustration of how digit distributions evolve from first- through later digits. We sampled 100,000 values from a normal distribution, N (0, 1.5), to create these digit distributions.

the NBL to apply [i.e., range from $1 - 1000000$;@10.1198/tast.2009.0005]. Third, these measures should not be subject to digit preferences, for example due to psychological preferences for rounded numbers. Fourth, any form of truncation undermines the NBL (Nigrini, 2015). Moreover, some research has even indicated humans might be sensitive to fabricating data that are in line with the NBL (**???**; Burns, 2009), immediately undermining the applicability of the NBL. Nonetheless, considering the four conditions for the NBL to apply, we preregistered that this method would not prove fruitful (**???**).

Terminal digit analysis

Terminal digit analysis is based on the principle that the rightmost digit is the most random digit of a number, hence, is expected to be uniformly distributed under specific conditions (**???**, **???**). Terminal digit analysis is conducted with a χ^2-test ($df = 10 - 1$) on the digit occurrence counts (including zero), where the observed frequencies are compared with the expected uniform frequencies. Tthe rule of thumb outlined by Agresti (2003) indicates at least 50 observations are required to provide a meaningful test of the terminal digit distribution ($n = I \times J \times 5$, with I rows and J columns). Terminal digit analysis was developed during the Imanishi-Kari case by (**???**; for a history of this decade long case, see Kevles, 2000).

As an example, Figure 1 depicts the digit counts for the first- through fifth digit of a random, normally distributed variable. The first- and second digit distributions are clearly non-uniform, whereas the third-, fourth-, and fifth digit distributions are uniformly distributed.

As such, the rightmost digit can be expected to be uniformly distributed if sufficient precision is provided (**???**). For our purposes, sufficient precision is determined as the terminal digit being at least the third leading digit [i.e., minimally 1.23 or 12.3 or 123].

Multivariate associations

True data occur within a web of relations, which can be observed in genuine data and easily forgotten while fabricating data. The multivariate relations between different variables arise from stochastic processes and are not readily known, hence difficult to take into account when someone wants to fabricate data. As such, using these multivariate associations to detect anomalies from genuine data might prove valuable.

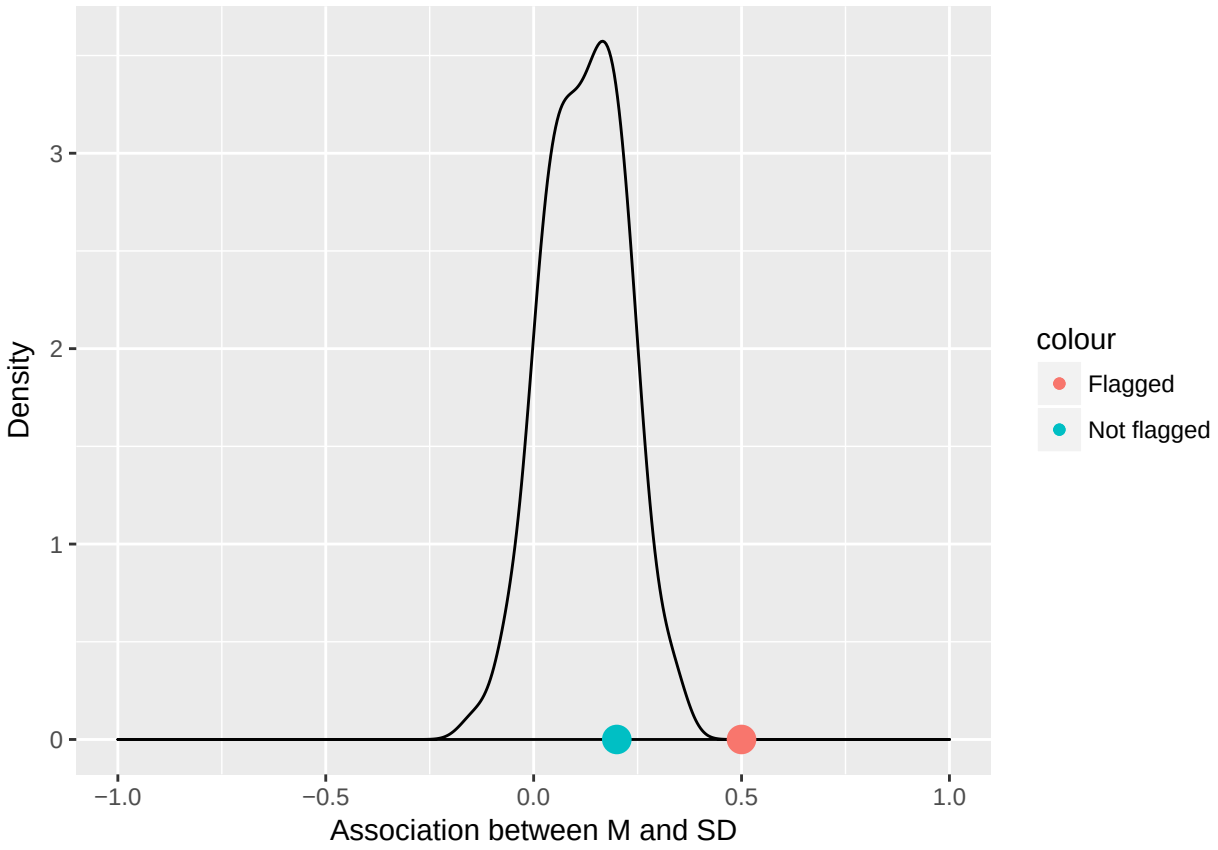


Figure 2: A fictitious distribution of observed association between Ms and SDs across 100 studies. The blue dot indicates the observed relation that is subject to screening for data anomalies.

The multivariate associations between different variables can be estimated from control data that are (assumably) genuine. For example, if the multivariate association between means (Ms) and standard deviations (SDs) is of interest, control data for that same measure can be collected from the literature, assuming the measure has been used in other studies. With these control data, a meta-analysis provides an overall estimate of the multivariate relation.

The multivariate relation from the genuine data is subsequently used to estimate how extreme the observed multivariate relation is. Consider the following fictitious example, regarding the multivariate association between Ms and SDs for a response latency task. Figure 2 depicts a simulated distribution of the association between Ms and SDs from the literature. The observed relation between Ms and SDs from two papers we want to (fictitiously) screen are 0.5 and 0.2. As such, we immediately see in Figure 2 that the former is flagged as being potentially anomalous (i.e., the red dot; two-tailed p-value 1.0274422×10^{-4} of the time), whereas the latter (blue dot) is not flagged (p-value: 1.0274422×10^{-4}).

Study 1 - detecting fabricated anchoring effects

We tested the performance of statistical methods to detect data fabrication in summary results with genuine- and fabricated summary results from four anchoring studies (Jacowitz & Kahneman, 1995; A. Tversky & Kahneman, 1974). The anchoring effect is a well-known psychological heuristic that uses the information in the question as the starting point for the answer, which is then adjusted to yield a final estimate of a quantity. For example 'Is the percentage of African countries in the United Nations more or less than [10% or 65%]?'. These questions yield mean responses of 25% and 45%, respectively (A. Tversky & Kahneman, 1974), despite

essentially posing the same factual question. A considerable amount of genuine datasets on this heuristic are freely available and we collected fabricated datasets within this study. This study was approved by the Tilburg Ethical Review Board (EC-2015.50).

Methods

We collected summary results for four anchoring studies: (i) distance from San Francisco to New York, (ii) population of Chicago, (iii) height of the Mount Everest, and (iv) the number of babies born per day in the United States (Jacowitz & Kahneman, 1995). Each of the four studies provided us with summary results for a 2 (low/high anchoring) $\times$ 2 (male/female) factorial design. Throughout this study, the unit of analysis is a set of summary statistics (i.e., means, standard deviations, and test results) for the four anchoring studies from one respondent. For current purposes, a respondent is defined as researcher/lab where the four anchoring studies' summary statistics originate from. All materials, data, and analyses scripts are freely available on the OSF (https://osf.io/b24pq) and a preregistration is available at https://osf.io/ejf5x (deviations are explicated in this report).

Data collection

We downloaded thirty-six genuine datasets from the publicly available Many Labs (ML) project (https://osf.io/pqf9r; Klein et al., 2014). The ML project replicated several effects across thirty-six locations, including the anchoring effect in the four studies mentioned previously. Considering the size of the ML project, the transparency of research results, and minimal individual gain for fabricating data, we assumed these data to be genuine. For each of the thirty-six locations we computed sample sizes, means, and standard deviations for each of the four conditions in the four anchoring studies (i.e., $3 \times 4 \times 4$) for each of the thirty-six locations. We computed these summary statistics from the raw ML data, which were cleaned using the original analysis scripts from the ML project.

Using quotum sampling, we collected thirty-six fabricated datasets of summary results for the same four anchoring studies. Quotum sampling was used to sample as many responses as possible for the available 36 rewards (i.e., not all respondents might request the gift card and count towards the quotum; one participant did not request a reward). The sampling frame consisted of 2,038 psychology researchers who published a peer-reviewed paper in 2015, as indexed in Web of Science (WoS) with the filter set to the U.S. We sampled psychology researchers to improve familiarity with the anchoring effect (Jacowitz & Kahneman, 1995; A. Tversky & Kahneman, 1974), for which summary results were fabricated. We filtered for U.S. researchers to ensure familiarity with the imperial measurement system, which is the scale of some of the anchoring studies (note: we found out several non-U.S. researchers were included because the WoS filter also retained papers with co-authors from the U.S.). WoS was searched on October 13, 2015. In total, 2,038 unique corresponding e-mails were extracted from 2,014 papers (due to multiple corresponding authors).

We invited a random sample of 1,000 researchers via e-mail to participate in this study on April 25, 2016 (invitation: https://osf.io/s4w8r). The study took place via Qualtrics with anonimization procedures in place (e.g., no IP-addresses saved). We informed the participating researchers that the study would require them to fabricate data and explicitly mentioned that we would investigate these data with statistical methods to detect data fabrication. We also clarified to the respondents that they could stop at any time without providing a reason. If they wanted, respondents received a $30 Amazon gift card as compensation for their participation if they were willing to enter their email address. They could win an additional $50 Amazon gift card if they were one of three top fabricators. The provided e-mail addresses were unlinked from individual responses upon sending the bonus gift cards. The full text of the Qualtrics survey is available at https://osf.io/w984b.

Each respondent was instructed to fabricate 32 summary statistics (4 studies $\times$ 2 conditions $\times$ 2 sexes $\times$ 2 statistics [mean and sd]) that fulfilled three hypotheses. We instructed respondents to fabricate results for the following hypotheses: there is (i) a main effect of condition, (ii) no effect of sex, and (iii) no interaction effect between condition and sex. We fixed the sample sizes to 25 per cell; respondents did not need to

Anchoring study - distance from San Francisco to New York

Expectations	Current result	Supported
Main effect of condition	F(1, 96) = 21.33, p < .001	✓
No main effect of gender	F(1, 96) = 0.03, p = 0.867	✓
No interaction effect of gender * condition	F(1, 96) = 0, p = 0.96	✓

			Mean (true distance: 2,906.5 miles)	Standard Deviation
Low anchor	The distance from San Francisco to New York City is longer than 1,500 miles. How far do you think it is?	Female	2562.12	956.35
		Male	2540.36	942.14
High anchor	The distance from San Francisco to New York City is shorter than 6,000 miles. How far do you think it is?	Female	3421.25	845.21
		Male	3380.98	932.56

Figure 3: Example of a filled in template spreadsheet used in the fabrication process of Study 1. Respondents fabricated data in the yellow cells, which were used to compute the results of the hypothesis tests. If the fabricated data confirm the hypotheses, a checkmark appeared in a green cell (one of four template spreadsheets available at https://osf.io/w6v4u/).

fabricate sample sizes. The fabricated summary statistics and their accompanying test results for these three hypotheses serve as the data to examine the properties of statistical tools to detect data fabrication.

We provided respondents with a template spreadsheet to fill out the fabricated data, in order to standardize the fabrication process without restraining the participant in how they chose to fabricate data. Figure 2 depicts an example of this spreadsheet (original: https://osf.io/w6v4u). We requested respondents to fill in the yellow cells with fabricated data, which includes means and the standard deviations for four conditions. Using these values, statistical tests are computed and shown in the "Current result" column instantaneously. If these results confirmed the hypotheses, a checkmark appeared as depicted in Figure 2. We required respondents to copy-paste the yellow cells into Qualtrics, to provide a standardized response format that could be automatically processed in the analyses.

Upon completing the fabrication of the data, respondents were debriefed. Respondents answered several questions about their statistical knowledge and approach to data fabrication and finally we reminded them that data fabrication is widely condemned by professional organizations, institutions, and funding agencies alike. We rewarded participation with a $30 Amazon gift card and the fabricated results that were most difficult to detect received a bonus $50 Amazon gift card.

Data analysis

We analyzed the genuine- and fabricated datasets for the four anchoring studies in four ways. First, we applied variance analyses to the reported variances of each of the four groups per study separately. Second, we applied the reversed Fisher method to the results of the gender and interaction hypotheses (i.e., nonsignificant results) across the four studies. Third, we combined the results from the variance analyses and the reversed Fisher method, using the original Fisher method (Fisher, 1925). Fourth, and not preregistered, we used effect size analysis (i.e., $1 - r$) that is a proxy of how extreme an effect is.

Specifically for the variance analyses, we deviated from the preregistration. Initially, we simultaneously analyzed the reported variances per study across the anchoring conditions. However, upon analyzing these values, we realized that the variance analyses assume that the reported variances are from the same population distribution, which is not necessarily the case for the anchoring conditions. Hence, we included two variance analyses per anchoring study (i.e., one for the high anchoring condition and one for the low anchoring condition). In the results we differentiate between these by using 'homogeneous' (across conditions) and 'heterogeneous' (separated for low- and high anchoring conditions).

For each of these statistical tests to detect data fabrication we carried out sensitivity and specificity analyses using Area Under Receiving Operator Characteristic (AUROC) curves. AUROC-analyses indicate the sensitivity (i.e., True Positive Rate [TPR]) and specificity (i.e., True Negative Rate [TNR]) for various decision

criteria (e.g., $\alpha = 0, .01, .02, ..., .99, 1$). With these AUROC-curves, informed decisions about optimal alpha levels can be made based on various criteria. In this case, we determine the optimal alpha level by finding that alpha level for which the combination of TPR and TNR were highest. For example, if $\alpha = .04$ results in $TPR = .30$ and $TNR = .70$, but $\alpha = .05$ results in $TPR = .5$ and $TNR = .5$, .05 was chosen as an optimal decision criterion based on the sample.

AUROC values indicates the probability that a randomly drawn fabricated- and genuine dataset can be correctly classified as fabricated and genuine (Hanley & McNeil, 1982). In other words, if $AUROC = .5$, correctly classifying a randomly drawn dataset in this sample is equal to a coin flip. For this setting, we will regard any AUROC $< .6$ as plainly insufficient for detecting data fabrication, $.6 \leq$ AUROC $< .7$ as failed, $.7 \leq$ AUROC $< .8$ as sufficient, $.8 \leq$ AUROC $< .9$ as good, and $.9 \leq$ AUROC ≤ 1 as excellent.

Results

The collected data included 36 genuine data from Many Labs 1 (https://osf.io/pqf9r; Klein et al., 2014) and 39 fabricated datasets (https://osf.io/e6zys; 3 participants did not participate for a bonus).

Figure 3 shows a group-level comparison of the genuine- and fabricated p-values and effect sizes (r). These group-level comparisons provide an overview of the differences between the genuine- and fabricated data (see also Akhtar-Danesh & Dehghan-Kooshkghazi, 2003). These distributions indicate little group differences between genuine- and fabricated data when nonsignificant effects are inspected (i.e., gender and interaction hypotheses). However, there seem to be large group differences when we required subjects to fabricate significant data (i.e., condition hypothesis). Considering this, we also investigated how well effect sizes perform in detecting data fabrication (not preregistered). In the following sections, we investigate the performance of such statistical methods to detect data fabrication on an respondent-level basis.

Performance of variance analysis to detect data fabrication

Table 3 indicates that both operationalizations (i.e., SD_z and $max - min_z$) show similar performance based on the AUROC. All in all, their performance ranges from 0.303 through 0.796. As such, there is considerable variation for the various applications of the variance analyses.

Table 3: *Table XX.* Diagnosticity of using variance analyses to detect data fabrication, depicted with the AUROC-value.

Method	AUROC SD_z	AUROC $max - min_z$
Homogeneous, all studies combined	0.423	0.303
Homogeneous, study 1	0.367	0.374
Homogeneous, study 2	0.421	0.446
Homogeneous, study 3	0.510	0.520
Homogeneous, study 4	0.540	0.542
Heterogeneous, all studies combined	0.770	0.758
Heterogeneous study 1, low anchor condition	0.644	0.644
Heterogeneous study 1, high anchor condition	0.438	0.438
Heterogeneous study 2, low anchor condition	0.750	0.750
Heterogeneous study 2, high anchor condition	0.614	0.614
Heterogeneous study 3, low anchor condition	0.667	0.667
Heterogeneous study 3, high anchor condition	0.650	0.650
Heterogeneous study 4, low anchor condition	0.796	0.796
Heterogeneous study 4, high anchor condition	0.556	0.556

Combining the variance analyses across the different studies improves performance. This is as expected,

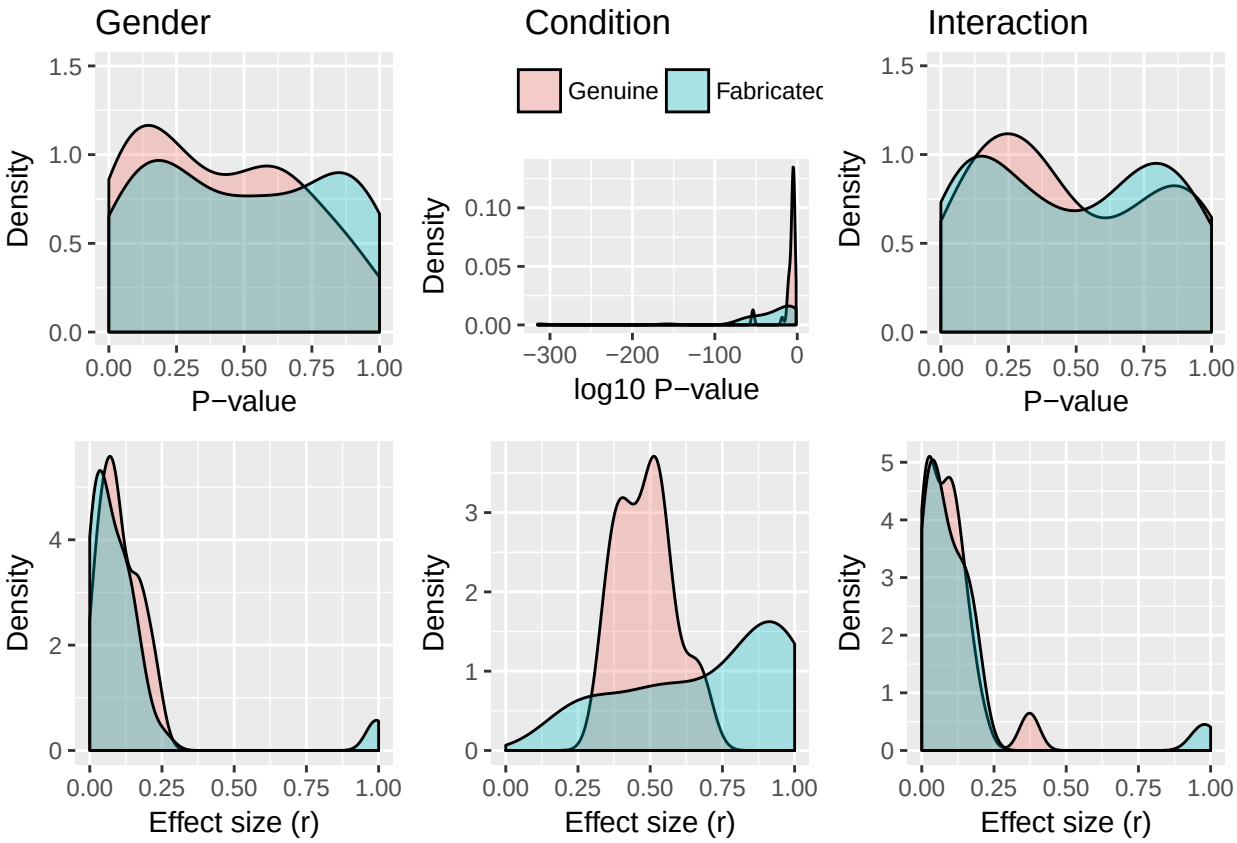


Figure 4: Overlay of density distributions for both genuine and fabricated data, per effect and type of result. We instructed respondents to fabricate nonsignificant data for the gender and interaction effects, and a significant effect for the condition effect.

considering that the sample size increases for the analyses (i.e., more reported variances are included) and that causes an increase in the statistical power to detect data fabrication.

More notably, combining the studies and taking the heterogeneous approach (i.e., separating anchoring conditions) greatly increases the performance to detect data fabrication considerably. Where the AUROC under homogeneous variances for $SD_z = 0.423$ ($max - min_z = 0.303$), under heterogeneous variances it increases to $SD_z = 0.77$ ($max - min_z = 0.758$). Further inspecting the heterogeneous variance of variances analysis indicates that no false positives occur until $\alpha = 0.13$, making this the optimal alpha level based on this sample (but note the small sample).

Performance of p-values analysis to detect data fabrication

Table 4 indicates that methods using nonsignificant p-values to detect data fabrication are hardly better than chance level in the current sample. We asked researchers to fabricate data for nonsignificant effect sizes, thinking they might be unable to produce uniformly distributed p-values. However, these results (and the density plot in Figure XX) indicate that widespread detection based on this is not promising.

Table 4: *Table XX.* Diagnosticity of using p-value analyses to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Reversed Fisher method gender hypothesis	0.521
Reversed Fisher method interaction hypothesis	0.535

Performance of combining variance- and p-value analyis to detect data fabrication

Table 5 indicates that combining the variance- and p-value methods provides little beyond the methods separately. The overall performance of this combination is driven by the variance analyses, given that the p-value analysis yields little more than chance classification. When combining the results from variance analyses per anchoring condition (i.e., 10 results, SD_z heterogeneous) and the p-value analyses, a minor improvement occurs over the heterogeneous variance analysis (all studies combined, $AUROC = 0.77$). However, this difference is negligible and potentially due to sampling error.

Table 5: *Table XX.* Diagnosticity of combining variance- and p-value analyses to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Combined Fisher test (3 results, SD_z homogeneous)	0.602
Combined Fisher test (3 results, SD_z heterogeneous)	0.736
Combined Fisher test (6 results, SD_z homogeneous)	0.643
Combined Fisher test (10 results, SD_z heterogeneous)	0.771

Performance of extreme effects to detect data fabrication

Table 6 indicates that using effect sizes (i.e., $1 - r$) is a simple but effective way to detect data fabrication ($AUROC = 0.744$). Compared to the variance analyses several sections ago, its performance in this sample is a bit worse (i.e., 0.744 compared to 0.77). However, it makes up for this by computational parsimony. Whereas the variance analyses require a considerable amount of effort to implement, computing the correlation and taking the inverse is a relatively simple task. Further inspecting the effect size approach to detecting data fabrication indicates that no false positives occur until $\alpha = 0.31$ (i.e., $r > 0.69$), making this the optimal

alpha level based on this sample (but note the small sample).

Table 6: *Table XX.* Diagnosticity of using effect sizes to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Effect sizes $(1 - r)$	0.744

Study 2 - detecting fabricated Stroop data

We investigated detecting data fabrication in raw data as an extension of Study 1. In essence, the procedure is similar: we asked actual researchers to fabricate data that they thought would go undetected. For Study 2 we included a face-to-face interview to qualitatively assess how data fabrication occurs. A preregistration of this study occurred during the seeking of funding (**???**) and during data collection (https://osf.io/fc35g).

To test the validity of statistical methods to detect data fabrication in raw data, we investigated raw data of a Stroop experiment (**???**). In the Stroop task, participants are asked to determine the color a word is presented in (i.e., word colors), but the word also reads a color (i.e., color words). The presented word color (i.e., 'red', 'blue', or 'green') can be either presented in the congruent color (e.g., 'red' presented in red) or an incongruent color (i.e., 'red' presented in green). The dependent variable in the Stroop task is the response latency (in this study milliseconds are used). Participants in actual studies are typically presented with a set of these, where the mean and standard deviation per condition serves as the raw data. The Stroop effect typically is computed as the difference in mean response latencies between the congruent and incongruent conditions.

Methods

Data collection

We collected twenty-one genuine datasets on the Stroop task from the Many Labs 3 project (https://osf.io/n8xa7/; **???**). Many Labs 3 (ML3) includes 20 participant pools from universities and one online sample (the original preregistration mentioned 20 datasets, accidentally overlooking the online sample; **???**). Similar to Study 1, we assumed these data to be genuine due to the minimal individual gains for fabricating data and the transparency of the project. Using the original raw data and analysis script from ML3 (https://osf.io/qs8tp/), we computed the mean (M) and standard deviation (SD) for the participant's response latencies in both the within-subjects conditions of congruent trials and incongruent trials. These also formed the basis for the template of the data that needed to be fabricated by the participants (see also Figure X). The Stroop effect was calculated as a t-test of the difference between the congruent and incongruent conditions ($H_0 : \mu = 0$).

We collected twenty-eight faked datasets on the Stroop task experimentally in a two-stage sampling procedure. First, we invited 80 Dutch and Flemish psychology researchers who published a peer-reviewed paper on the Stroop task between 2005-2015 as available in the Thomson Reuters' Web of Science database. We selected Dutch and Flemish researchers to allow for a face-to-face interview on how the data were fabricated. We chose the period 2005-2015 to prevent a drastic decrease in the probability that the corresponding author would still be addressable via the given email. The database was searched on October 10, 2016 and 80 unique e-mails were retrieved from 90 publications. Only two of these 80 participated in the study; we subsequently implemented a second sampling stage where we collected e-mails from all PhD-candidates, teachers, and professors of psychology related departments at Dutch universities. This resulted in 1659 additional unique e-mails that we subsequently invited to participate in this study. Due to a malfunction in Qualtrics' quotum sampling, we oversampled, resulting in 28 participants instead of the originally intended 20 participants.

Stroop Task

Test of condition effect

		t	df	p	Supported?	
		-20376.57	24	<.001	✓	
	Congruent (milliseconds)			Incongruent (milliseconds)		
id	Mean	SD	Number of trials	Mean	SD	Number of trials
1	150	21	30	300	300	30
2	152	21	30	304	304	30
3	154	21	30	308	308	30
4	156	22	30	312	312	30
5	158	22	30	316	316	30
6	160	22	30	320	320	30
7	162	22	30	324	324	30
8	164	22	30	328	328	30
9	166	22	30	332	332	30
10	168	22	30	336	336	30
11	170	23	30	340	340	30
12	172	23	30	344	344	30
13	174	23	30	348	348	30
14	176	23	30	352	352	30
15	178	23	30	356	356	30
16	180	23	30	360	360	30
17	182	23	30	364	364	30
18	184	23	30	368	368	30
19	186	24	30	372	372	30
20	188	24	30	376	376	30
21	190	24	30	380	380	30
22	192	24	30	384	384	30
23	194	24	30	388	388	30
24	196	24	30	392	392	30
25	198	24	30	396	396	30

Figure 5: Example of a filled in template spreadsheet used in the fabrication process for Study 2. Respondents fabricated data in the yellow cells and green cells, which were used to compute the results of the hypothesis test of the condition effect. If the fabricated data confirm the hypotheses, a checkmark appeared. This template is available at https://osf.io/2qrbs/.

Each participant received instructions on the data fabrication task via Qualtrics but was allowed to fabricate data until the face-to-face interview took place. In other words, each participant could take the time they wanted/needed to fabricate the data as extensively as they liked. Each participant received downloadable instructions (original: https://osf.io/7qhy8/) and the template spreadsheet via Qualtrics (see Figure X; https://osf.io/2qrbs/). The interview was scheduled via Qualtrics with JGV, who blinded the rest of the research team from the identifying information of each participant and the date of the interview. All interviews took place between January 31 and March 3, 2017. To incentivize researchers to participate, they received 100 euros for participation; to incentivize them to fabricate (supposedly) hard to detect data they could win an additional 100 euros if they belonged to one out of three top fabricators. The contents of the interview were transcribed for further research on qualitatively assessing how researchers might fabricate experimental data.

Data analysis

To detect data

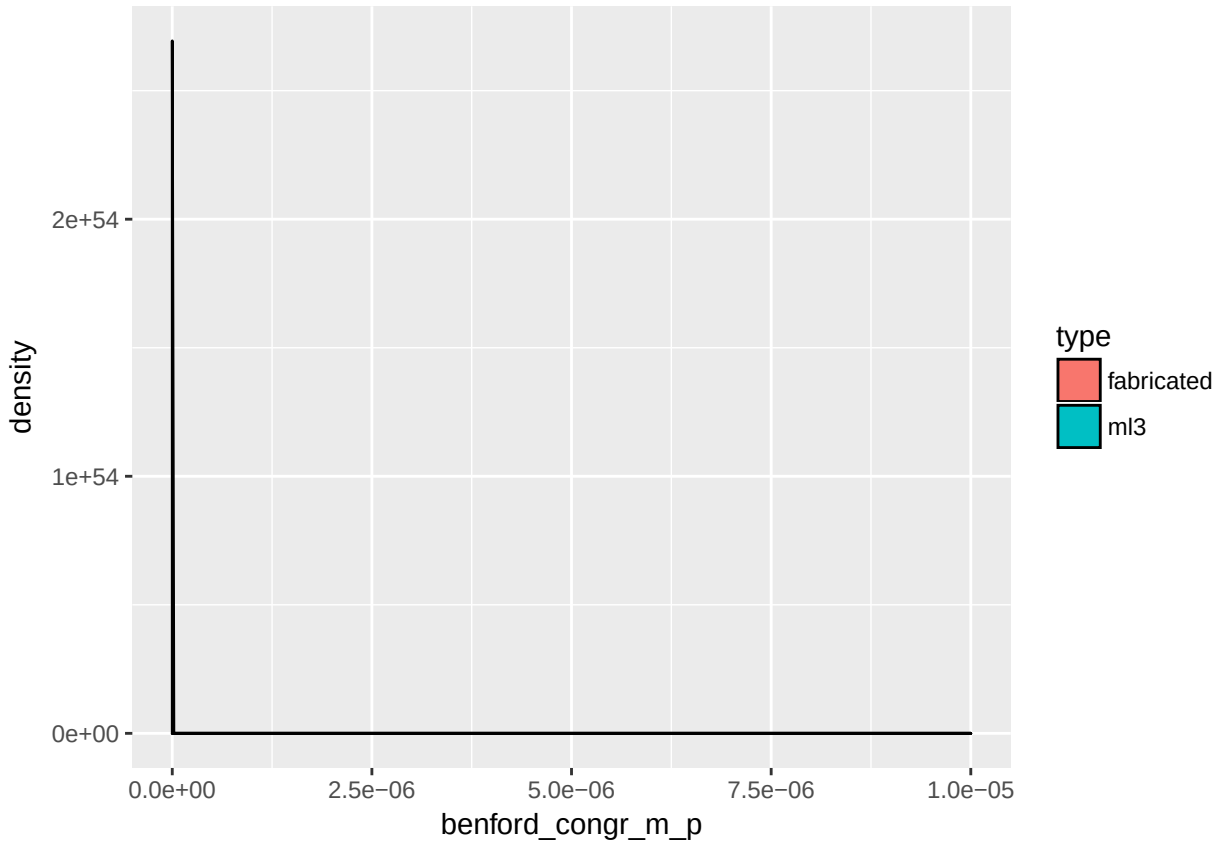
Results

Performance of NBL to detect data fabrication

Table 7: *Table XX*. Diagnosticity of using the Newcomb-Benford law (NBL) to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
NBL, congruent means	0.500
NBL, congruent SDs	0.531
NBL, incongruent means	0.500
NBL, incongruent SDs	0.321

```
ggplot(dat, aes(x = benford_congr_m_p)) + geom_density(aes(fill = type)) + xlim(0, .00001)
```



Performance of terminal digit analysis to detect data fabrication

Table 8: *Table XX.* Diagnosticity of using terminal digit analysis to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Terminal digit analysis, congruent means	0.002
Terminal digit analysis, congruent SDs	0.043
Terminal digit analysis, incongruent means	0.018
Terminal digit analysis, incongruent SDs	0.014

Performance of variance analysis to detect data fabrication

Table 9: *Table XX.* Diagnosticity of using variance analysis to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Variance analysis, congruent condition	0
Variance analysis, incongruent condition	0

Performance of multivariate associations to detect data fabrication

Table 10: *Table XX.* Diagnosticity of using multivariate associations to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Multivariate association means and SDs, congruent condition	0.749
Multivariate association means and SDs, incongruent condition	0.837
Multivariate association means, across conditions	0.594
Multivariate association SDs, across conditions	0.719

Performance of combining

Table 11: *Table XX.* Diagnosticity of using variance analysis to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Fisher combination of terminal, variance, and multivariate	0.554

Performance of effect sizes

Table 12: *Table XX.* Diagnosticity of using variance analysis to detect data fabrication, depicted with the AUROC-value.

Method	AUROC
Effect size $(1 - r)$	0.984

Discussion

Session info

```
sessionInfo()
```

```
## R version 3.4.0 (2017-04-21)
## Platform: x86_64-redhat-linux-gnu (64-bit)
## Running under: Fedora 25 (Workstation Edition)
##
## Matrix products: default
## BLAS/LAPACK: /usr/lib64/R/lib/libRblas.so
##
## locale:
##  [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
##  [3] LC_TIME=en_US.UTF-8        LC_COLLATE=en_US.UTF-8
##  [5] LC_MONETARY=en_US.UTF-8    LC_MESSAGES=en_US.UTF-8
##  [7] LC_PAPER=en_US.UTF-8       LC_NAME=C
##  [9] LC_ADDRESS=C               LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
```

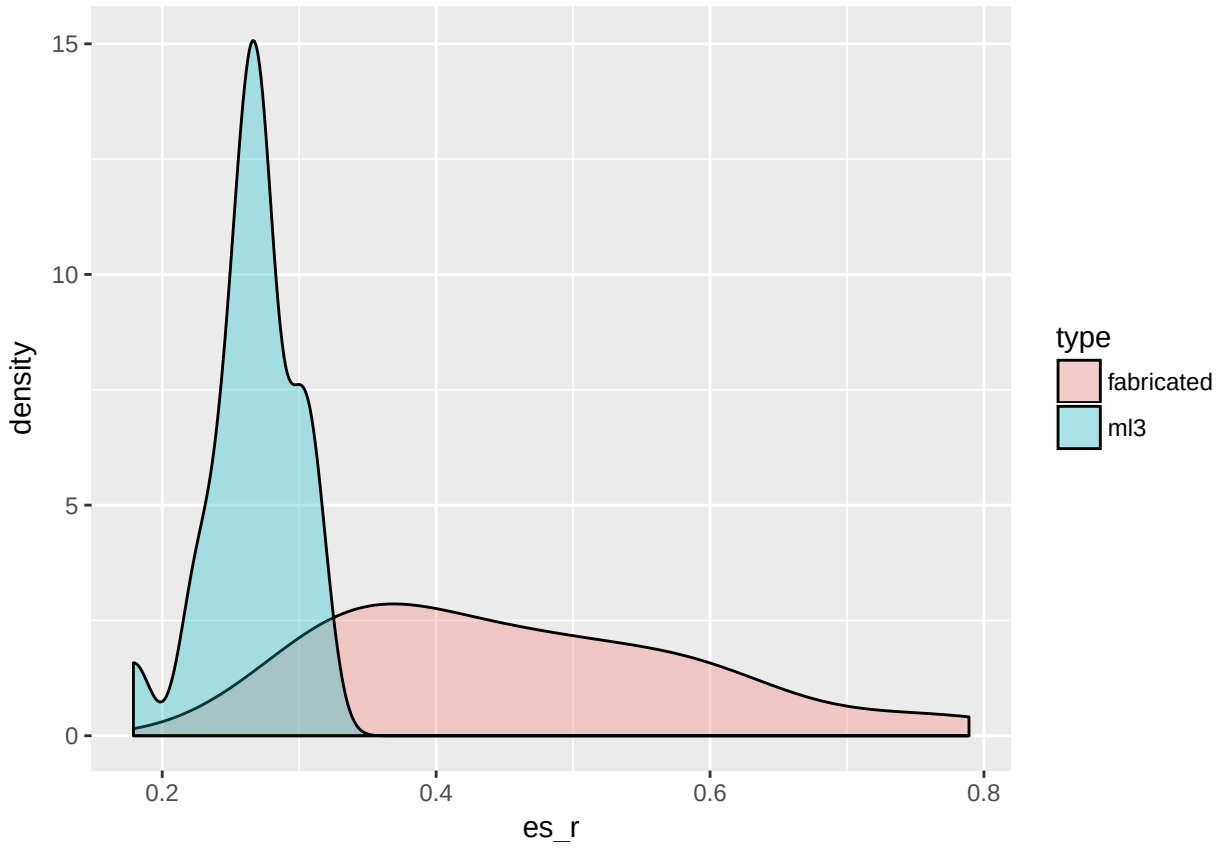


Figure 6: The effect size distributions from Many Labs 3 and those fabricated by the participants

```
##
## other attached packages:
##  [1] stringr_1.2.0     plyr_1.8.4        metafor_2.0-0
##  [4] Matrix_1.2-9      reshape2_1.4.2    dplyr_0.7.1
##  [7] data.table_1.10.4 lsr_0.5           effects_3.1-2
## [10] car_2.0-19        httr_1.2.1        xtable_1.7-1
## [13] gridExtra_2.2.1   ggplot2_2.2.1     latex2exp_0.4.0
## [16] foreign_0.8-67    knitr_1.16        pROC_1.10.0
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_0.12.11     highr_0.6        bindr_0.1        nloptr_1.0.4
##  [5] compiler_3.4.0   tools_3.4.0      digest_0.6.12    lme4_1.1-13
##  [9] evaluate_0.10.1  tibble_1.3.3     gtable_0.2.0     nlme_3.1-131
## [13] lattice_0.20-35  pkgconfig_2.0.1  rlang_0.1.1      yaml_2.1.14
## [17] bindrcpp_0.2     rprojroot_1.2    grid_3.4.0       nnet_7.3-12
## [21] glue_1.1.1       R6_2.2.1         rmarkdown_1.6    minqa_1.2.4
## [25] magrittr_1.5     backports_1.1.0  scales_0.4.1     htmltools_0.3.6
## [29] MASS_7.3-47      splines_3.4.0    assertthat_0.2.0 colorspace_1.3-2
## [33] labeling_0.3     stringi_1.1.5    lazyeval_0.2.0   munsell_0.4.3
```

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