TED-On: A Total Error Framework for Digital Traces of Human Behavior on Online Platforms

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Abstract

Peoples’ activities and opinions recorded as digital traces online, especially on social media and other web-based platforms, offer increasingly informative pictures of the public. They promise to allow inferences about populations beyond the users of the platforms on which the traces are recorded, representing real potential for the Social Sciences and a complement to survey-based research. But the use of digital traces brings its own complexities and new error sources to the research enterprise. Recently, researchers have begun to discuss the errors that can occur when digital traces are used to learn about humans and social phenomena. This article synthesizes this discussion and proposes a systematic way to categorize potential errors, inspired by the Total Survey Error (TSE) Framework developed for survey methodology. We introduce a conceptual framework to diagnose, understand, and document errors that may occur in studies based on such digital traces. While there are clear parallels to the well-known error sources in the TSE framework, the new “Total Error Framework for Digital Traces of Human Behavior on Online Platforms” (TED-On) identifies several types of error that are specific to the use of digital traces. By providing a standard vocabulary to describe these errors, the proposed framework is intended to advance communication and research concerning the use of digital traces in scientific social research.

1 Introduction

When investigating social phenomena, for decades, the empirical social sciences have relied on surveying samples of individuals taken from well-defined populations as one of their main data sources, e.g., general national populations. An accompanying development was the constant improvement of methods as well as statistical tools to collect and analyze survey data (Groves, 2011). These days, survey methodology can be considered an academic discipline of its own (Joye et al., 2016). It has distilled its history of research dedicated to identifying and analyzing the various errors that occur in the statistical measurement of collective behavior and attitudes as well as generalizing to larger populations into the Total Survey Error framework (TSE). This framework provides a conceptual structure to identify, describe, and quantify the errors of survey estimates (Biemer, 2010; Groves and Lyberg, 2010; Weisberg, 2009; Groves et al., 2009). While not existing in one single canonical form, the tenets of the TSE are stable and provide survey designers with a guideline for balancing cost and efficacy of a potential survey and, not least, a common vocabulary to identify error sources in their research design from sampling to inference. In the remainder, we will refer to the concepts of the TSE as put forth by Groves et al. (2009, 48).

Icons used in this image have been designed by Becris, Elias Bikbulatov and Pixel perfect from https://www.flaticon.com.
Recently, surveys have come to face various challenges, such as declining participation rates, while simultaneously, there has been a growth of alternative modes of data collection (Groves, 2011). In the course of continuous digitalization, this often includes new types of data that have not been collected in a scientifically pre-designed process but are captured by web-based platforms and other digital technologies such as smartphones, fitness devices, RFID mass transit cards or credit cards. These digital traces of human behavior become increasingly available to researchers. It is especially the often easily accessible data from social media and other platforms on the World Wide Web that has become of heightened interest to scientists in various fields aiming to explain or predict human behavior (Watts, 2007; Lazer et al., 2009; Salganik, 2017). Beside studying platforms per se to understand user behavior on and societal implications of, e.g., a specific web site (see DiMaggio et al., 2001), digital trace data promises inferences to broad target populations similar to surveys, but at a lower cost, with larger samples (Salganik, 2017). In fact, research based on digital trace data is frequently referred to as “Social Sensing” – i.e., studies that repurpose individual users of technology and their traces as sensors for larger patterns of behavior or attitudes in a population (An and Weber, 2015; Sakaki, Okazaki, and Matsuo, 2010). In addition to increasing scale and decreasing costs, digital traces also capture quasi-immediate reactions to current events (e.g., natural disasters) which makes them particularly interesting for studying reactions to unforeseeable events which surveys can only ask about in retrospect.

However, digital traces come with various challenges such as bias due to self-selection, platform affordances, data recording and sharing practices, heterogeneity, size, etc., raising epistemological concerns Tufekci (2014); Olteanu, Weber, and Gatica-Perez (2016); Ruths and Pfeffer (2014); Schober et al. (2016). Another major hurdle is created by uncertainty about exactly how the users of a platform differ from members of a population to which researchers wish to generalize, which can change over time. While not all of these issues can be mitigated, they can be documented and examined for each particular study that leverages digital traces, to understand issues of reliability and validity (e.g., Lazer (2015)). Only by developing a thorough understanding of the limitations of a study can we make it comparable with others. Moreover, assessing the epistemic limitations of digital trace data studies can often help illuminate ethical concerns in the use of these data (e.g., Olteanu, Weber, and Gatica-Perez (2016); Mittelstadt et al. (2016); Jacobs and Wallach (2019)).

Our Contributions. Our work adds to the growing literature on identifying errors in digital trace based research (Olteanu et al., 2019; Tufekci, 2014; Hsieh and Murphy, 2017; Ruths and Pfeffer, 2014; Lazer, 2015), by highlighting these errors through the lens of survey methodology and leveraging its systematic approach. Based on the TSE perspective, we propose a framework that covers the known error sources potentially involved when using digital trace data, the Total Error Framework for Digital Traces of Human Behavior on Online Platforms (TED-On). This allows researchers to characterize and analyze the errors that occur when using data from online platforms to make inferences about a theoretical construct (see Figure 1) in a larger target population beyond the platforms’ users. By connecting errors in digital trace-based studies and the TSE framework, we establish a common vocabulary for social scientists and computational social scientists to help them document, communicate and compare their research. The TED-On, moreover, aims to foster critical reflection on study designs based on this shared vocabulary, and consequently better documentation standards for describing design decisions. Doing so helps lay the foundation for accurate estimates from web and social media data. In our framework we map errors to their counterparts in the TSE framework, and, going beyond previous approaches which leverage the TSE perspective (Amaya, Biemer, and Kinyon, 2020; Japec et al., 2015), describe new types of errors that arise specifically from the idiosyncrasies of digital traces online, and associated methods. Further, we adopt the clear distinction between measurement and representational inference (cf. Figure 1), as proposed by Groves et al. (2009). Through running examples (and a case study in Supplementary Materials, Section 3) that involve different online platforms including Twitter and Wikipedia, we demonstrate how errors at every step can, in principle, be discovered and characterized when working with web and social media data. This comprises measurement from heterogeneous and unstructured sources common to digital trace data, and particularly the challenge of generalizing beyond online platforms. While our framework is mainly focused on web and social media

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1 Researchers refer to digital trace data with different names including social data (Olteanu et al., 2019; Alipourfard, Fennell, and Lerman, 2018) and big data (Salganik, 2017; Pasek et al., 2019).
data, it is in principle applicable to other sources of digital trace data of humans as well, such as mobility sensors, transaction data or cell phone records. We discuss such further applications at the end of this paper.

2 Background: The Total Survey Error and its Relevance to Digital Trace Data

In this section, we explain the differences and commonalities between a survey-based and a digital trace data study of human behavior or attitudes. We do so to develop an understanding of the limitations and strengths of both approaches to conduct social science research and, thus, the sources and types of errors that affect both approaches. We also explore the Total Survey Error Framework and how it helps survey designers document their studies.

While both processes have some overlapping stages (see section 2.2), the primary point of difference is that digital trace data is typically nonreactive due to the lack of a solicitation of (often standardized) responses. In survey-based research, careful planning is required to come up with questions that measure the construct of interest and a sensible sampling frame from which a (random) sample of individuals, households or other units is drawn. Next, an interviewer- or self-administered survey is conducted and the responses are collected, which are then used to estimate the population parameter. In this research design, though, respondents are well aware that they are subject to a scientific study, entailing several potential consequences, such as social desirability bias in answers. And, at each stage of the survey life cycle, data quality can be compromised due to a multitude of errors (for more information, see section 2.1). When relying on digital trace data collected via a web platform, there is no need for developing a sampling design or interviewing respondents. Here, individuals’ traces (or a subset of traces after querying) are readily available. Hence, individuals are usually not aware that they are subject to a scientific investigation, which has the advantage that researchers can directly observe how users behave rather than relying on self-reported data. It has the disadvantage that researchers may run the risk of misunderstanding these traces, as they are produced in complex and heterogeneous technical and social contexts. This can be avoided in a survey by constructing effective questionnaires and controlling the survey situation to some extent. Much of the divergence between surveys and digital trace based study rests on how we may effectively use potentially noisy, unsolicited traces to understand theoretical constructs while keeping in mind that these traces may not be effective proxies for that construct. In the next subsection, we describe a typical survey workflow through the lens of the TSE.

2.1 The Total Survey Error Framework

In survey research, errors can be described and systematized by focusing on the source of errors, most prominently the distinction between measurement errors and representation errors (Groves et al., 2009).2 For our framework, we mostly focus on Groves et al.’s approach in making an overall distinction between errors in, firstly, defining and measuring a theoretical construct with chosen indicators (measurement errors) and, secondly, the errors arising when inferring from a sample to the target population (representation errors) as illustrated in Figure 2 (Groves et al., 2009). We adopt this specific distinction as it is helpful in conceptually untangling different fallacies plaguing surveys as well as related research designs with non-designed, non-reactive, and non-probabilistic digital data. The reader should keep in mind that errors can be both systematic (biased) or randomly varying at every step of the inferential process we describe in the remainder.

Measurement errors, from a survey methodological perspective, can be regarded as the “[…] departure from the true value of the measurement as applied to a sample unit and the value provided” (Groves et al., 2009, 52). With respect to the “Measurement” arm in Figure 2 representing these errors, the first step of a survey-driven – and any similar study – requires defining the theoretical construct of interest and establishing a theoretical link between the captured data and the construct (Howison, Wiggins, and Crowston, 2011). Survey researchers usually start by defining the main construct of interest (e.g., “political leaning”, “personality”) and potentially related constructs (e.g., “political interest”). This is followed by the development or reuse of scales (i.e., sets of questions and items) able to measure the construct adequately, establishing validity. In developing scales, content validity, convergent construct validity, discriminant construct validity, internal consistency as well as other quality marks are checked (cf. Straub, Boudreau, and Gefen (2004)). The design of items usually follows a generally fixed and pre-defined research question and theorized constructs (notwithstanding some adaptations after pre-testing), followed by fielding the actual survey. Groves et al. (2009) further point out “measurement error” (not to be confused with the measurement error arm of the TSE), which we denominate response error here for clarity. It arises during the solicitation of actual information in the field even when an ideal measurement has been found. I.e., a respondent understands a set of items as intended, but either cannot (usually trough recall problems) or does not want to (e.g. social desirability) answer truthfully. Lastly arise processing errors introduced when processing data, such as coding textual answers into quantitative indicators and data cleaning. Besides validity, individual responses may also suffer from variability over time or between participants, contributing to low reliability.

Representation errors are the second source of error which are concerned with the question of how well a survey estimate generalizes to the target population. Representation errors consist of coverage error, sampling error, nonresponse

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1Icons used in this image have been designed by Hadrien, Becris, Freepik, Smartline, Pixel perfect, pixelmeetup, eucalyp, Gregor Cresnar, and prettycons from www.flaticon.com

2We refer to error as the difference between the obtained value and the true value we want to measure, while bias refers to systematic errors, following the definitions in Weisberg’s ‘The Total Survey Error Approach’, p.22 (Weisberg, 2009)
error and adjustment error (Groves et al., 2009) and contribute to the external validity or generalizability of a study.

Survey design begins its quest for unbiased representation by clearly defining the target population that the construct of interest should be measured for/inferred to, e.g., the national population of a nation-state. Then, a sampling frame is defined, the best approximation of all units in the target population, e.g., telephone lists or (imperfect) population registers, resulting in under- or over-coverage of population elements, constituting coverage error. Ineligible units might add noise to the sampling frame, such as business telephone numbers. Note that coverage error “exists before the sample is drawn and thus is not a problem arising because we do a sample survey” (Groves et al., 2009). When actually drawing a (random) sample employing the previously defined sampling frame, “one error is deliberately introduced into sample survey statistics”, as Groves et al. (2009, 56) put it. Mostly due to financial constraints, but also due to logistical infeasibilities, it is not possible to survey every element in the sampling frame. By ignoring these elements, the sample statistics will most likely deviate from the (unobservable) sampling frame statistics, thereby introducing a sampling error. The sampling error can be decomposed into two components: sampling variance, the random part, and sampling bias, the systematic part. The sampling variance is a consequence of randomly drawing a set of \( n \) elements from a sampling frame of size \( N \). Applying a simple random sample design, \( \binom{N}{n} \) samples can be realized. Since each sample realization is composed of a unique composition of elements, sampling variance is introduced. Sampling bias as the second component of sampling error comes into play when the sampling process is designed and/or executed in such a way that a subset of units is selected from the sampling frame but giving some members of the frame systematically lower chances to be chosen than others. Of course, sampling error can only arise when there is no feasible way of reaching all elements in the sampling frame – if one could access all elements of the complete sampling frame with minimal cost, sampling error would not occur.

Further, if chosen individuals drawn as part of the sample refuse to answer the whole survey, we speak of unit nonresponse errors. While in most cases providing insufficient responses to items hinders valid inferences regarding the topical research questions, nonresponse to demographic items can also hinder post-survey adjustment of representation errors. Lastly, Groves et al. (2009) list adjustment error, occurring when reweighting is applied post-survey to under- or over-represented cases due to any of the representation errors described above. The reweighting is usually based on socio-demographic attributes of individuals and often their belonging to a certain stratum.

### 2.2 Research with Digital Trace Data

While digital traces are often used to measure the same things as surveys do, they proceed differently. Like in a survey, the researcher defines the theoretical construct and the ideal measurement that will quantify it. However, in survey-based research, the measurement instrument can be constructed tailored to the research question, including a stimulus (question). In contrast, the researcher has less control over digital-trace-based measurement instruments that need to work with already existing traces, the stimuli for which are not researcher-administered. The researcher then picks the source of the digital traces by selecting one or more platforms (often, on the Web). The chosen platform(s) act(s) as the sampling frame. Depending on data accessibility, all “users” on the platform, as well as the “traces” produced by them, may be available to the researcher. These together constitute the digital traces of interest. Traces in our definition refer to (i) user-generated content (Johnson, Safadi, and Faraj, 2015), containing rich – but often noisy – information in form of textual and visual content (Schober et al., 2016) (e.g., tweets, photos, details in their profile biography); and to (ii) records of user activity which provide signals about users who do not post content, but interact with existing posts and other content, e.g., by “liking”, viewing or downloading.

Traces are in general generated by identifiable users that can be reasonably believed to represent a human actor (or sometimes, a group of human actors). Such users are most frequently platform accounts or user profiles, but might also be IP addresses. In alternative settings, they might be bank accounts, smart devices or other proxies for human actors. Users representing organisations or automated programs run the risk of being mistaken as suitable proxies for human actors and might have to be filtered out (cf. Section 3.4). Users typically emit various traces over time and carry additional attribute information about themselves (gender or location of the account holder, type of account, etc.).

Note that while traces are produced by users, these concepts are not mappings of responses and respondents to digital trace data. Instead, traces are produced without researcher-induced stimuli, and users do neither always stand for a single element of the (human) target population nor are they always observable. In fact, traces cannot always be linked to a user account or another reasonably persistent proxy of a human actor, e.g., in systems that only link traces to dynamically assigned IPs or other quasi-anonymous identifiers (such as Wikipedia pageviews, or single online shop purchases with links to accounts). Further, the link from traces and users to the units of the target population – in order to make inferences about them – can be constructed in different ways. This at times limits the understanding of what the eventual aggregate statistic represents in digital trace studies, since it might be (a) an aggregate of traces collected inside a particular boundary without specifying a concrete set of users to be collected (e.g., all traces in a certain time period or at a certain location), or (b) take into account these users, e.g., by aggregating social media posts per user profile and reweighting them by attached socio-
demographical metadata. If only traces are used, they cannot be assumed to be independent traces from an equal amount of human “emitters” or “sensors”. This can lead to methodological as well as epistemological issues.

For data collection, and in contrast to surveys, researchers can then (i) chose to either sample traces or users, and (ii) frequently have access to the entire sampling frame of a platform (in this case, one might even speak of a consensus of the platform). Therefore, there is often no need for sampling due to logistical infeasibility, as is typically done in surveys - and “sample” has to be understood in this light. Though the entire sampling frame is technically collectable, the researcher often still needs to create a subset of traces or users since it is no necessarily storable or processable because of its volume, due to restrictions imposed by data providers or other legal or ethical restrictions. Depending on their needs and the construct being studied, the researcher thus devises a data collection strategy, which usually involves a set of queries that select a specific portion the platform data, producing the final data subset that will be used for the study.

The traces and the users that make up this subset are usually further filtered or preprocessed, including labeling (or coding). In this regard, digital trace data is similar to survey data based on open-ended questions, which also requires a considerable amount of preprocessing before it can be statistically analyzed. However, due to commonly very high volume of digital traces, preprocessing of these data is almost exclusively done via automated methods that rely on heuristics or (semi-)supervised machine learning models. Depending on the subject of analysis, data points are then aggregated and analysed, to produce the final estimate, as is done for survey estimates.

Note that TED-On is centered around an idealized and somewhat prototypical abstraction of the research process for digital traces. As there is no unified convention for how to conduct such research – potentially involving a wide range of data and methods – the actual workflows may differ from this abstraction, e.g., depending on disciplinary backgrounds. E.g., in an ideal world, the research design pipeline as outlined in Figure 1 would be followed sequentially, whereas in reality, researchers will start their process at different points in the pipeline, e.g., get inspiration in form of an early-stage research question through a platform’s available data and its structure, and then iteratively refine the several steps of their research process. This is a notably different premise vis-à-vis survey-based research, since data is largely given by what a platform stores and what is made available to the researcher – hence, the theoretical fitting often happens post hoc (Howison, Wiggins, and Crowston, 2011). A major difficulty is that in order to avoid measurement errors, instead of designing a survey instrument, digital trace studies must consider several steps of the process at once: (i) definition of a theoretical construct aligned with an ideal measurement (ii) the platform to be chosen, (iii) ways to extract (subsets of) data from the platform, (iv) ways to process the data, and (v) the actual measurement of the construct through manifest indicators extracted from the data (Lazer, 2015), (vi) understand for whom or what conclusions are being drawn and how that population relates to the traces observed in the digital traces (Jungherr, 2017).

2.3 Ethical Challenges.

For a more comprehensive reflection than we can offer here, we point towards the growing body of research specializing on ethical dimensions of working with data from web and social media, such as work by Zimmer and Kinder-Kurlanda (2017) and Olteanu et al. (2019). There are also initiatives to provide researchers with practical guidance for ethical research design (e.g., Frankze et al. (2019) for the Association of Internet Researchers). In our context it is important to note that applying ethical decision-making might potentially limit options in research design – which could contribute to error sources in some cases. For example, research is already often based on only those (parts of) platform data which are publicly available, which may add to errors on the platform selection and data collection levels. Users have typically not consented to be part of a specific study and may not be aware that researchers are (potentially) utilizing their data Fiesler and Proferes (2018), but greater awareness of research activities may also lead to changing user behaviour (or specific groups of users withdrawing from certain activities). Although research in this area is typically not targeted at individual users but rather large collections of aggregated user data, research designs may still have ethical impact on certain groups (or even on the individual level). For example, automatic classification of user groups with machine learning methods can lead to reinforcement of social inequities, e.g., for racial minorities (see below for “user augmentation error”). In the future it will be interesting to see how new approaches for applying informed consent practices to digital trace data can be adapted, e.g. via data donations. It has also been shown that it may not always be possible to prevent de-anonymizing attempts, which might even aggravate as research procedures and their potential errors are becoming more open and being described in greater detail.

3 A Total Error Framework for Digital Traces of Human Behavior on Online Platforms (TED-On)

In the remainder, we map the different stages of research using digital traces with those of a survey-based research pipeline where appropriate. Finding equivalencies between the stages facilitates examining errors in digital trace based analysis through the lens of the TSE. Finally, we account for the divergences between the two paradigms and accordingly adapt the error framework to describe and document the different kinds of measurement and representation errors lurking in each step (Figure 1).

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5 The best-known example: Twitter’s restricted-access streaming APIs which enforce a platform-provided “random sample” as described by Twitter.

6 We use the term ‘platform data’ to refer to users or traces generated by users on that particular platform for the rest of the paper.
3.1 Construct Definition

(Theoretical) Constructs are abstract ‘elements of information’ (Groves et al., 2009) that a scientist attempts to measure by recording responses through the actual (survey) instrument and finally, by analysis of the responses. A non-definition or under-definition of the construct or a mismatch between the construct and the envisioned measurement corresponds to issues of validity. Given that digital trace data from any particular platform is not specifically produced for the inferential study, researchers must establish a link between the behavior that is observable on the platform and the theoretical construct of interest. The first step of transforming a construct into a measurement involves defining the construct; this requires thinking about competing and related constructs, in the best case rooted in theory. Next, researchers have to think about how to operationalize the construct. This entails deliberating about whether a potential ideal measurement sufficiently captures the construct from the given data and if the envisioned measurement does not also – or instead – capture other constructs, i.e., think about convergent vs. discriminant validity of a measurement (Jungherr et al., 2017).

Since digital trace based studies might proceed in a non-linear fashion, researchers may or may not begin their study with a theoretical construct and a pre-defined measurement in mind. Sometimes a researcher might start with a construct but reevaluate it, and the corresponding measurement, throughout the study depending on the nature of the digital traces. Since the data is largely given by what the platform/system stores, what is available for the public and/or what can be accessed via Application Programming Interfaces (APIs), it may require rethinking the original construct and its definition. Another alternative, which Salganik (2017) describes as the “ready-made” approach, is to start with a platform or dataset, and then envision constructs that can be studied from that particular platform or dataset.

**Example: Construct Definition**

An example of a construct that researchers have been aiming to measure with digital trace data is presidential approval. Whereas in a survey one expresses the defined construct as directly as possible in the questionnaire (“Do you approve or disapprove of the way Donald Trump is handling his job as president?”) a digital trace data researcher may consider the act of tweeting about the president positively to be equivalent to approval (O’Connor et al., 2010; Pasek et al., 2019). While positive mentions may indicate approval, researchers should also investigate whether the tweets focus on the presidential role and in fact constitute the ideal – or at least an appropriate – measurement. Due to the unsolicited nature of Twitter data, it can be difficult to disentangle if the tweets are targeted towards presidential or personal activities or features. E.g., while comments about the president’s private life may indirectly impact approval ratings, they do not directly measure how the president is handling his job, thereby weakening the measurement.

### 3.2 Platform Selection

In selecting a platform, the researcher needs to ensure the general existence of a link between digital traces that are observable on the platform and the theoretical construct of interest. They, however, also need to account for the impact of the platform and its community on the observable traces and the (likely) divergence between the target population of interest and the platform population. Below, we discuss the errors that may occur due to the chosen platform(s).

**Platform Affordances Error.** Just as in survey design, content and collection modes may influence responses, the behavior of users and their traces are impacted by (i) platform-specific sociocultural norms as well as (ii) the platform’s design and technical constraints (Wu and Taneja, 2020), leading to measurement errors which we together summarize as platform affordances error.

For example, Facebook recommends “people you may know”, thereby impacting the friendship links that Facebook users create (Malik and Pfeffer, 2016), while Twitter enforcing a 280-character limit on tweets influences the writing style of Twitter users (Gligorić, Anderson, and West, 2018). “Trending topic” features can shift users’ attention, and feedback buttons may deter utterances of polarizing nature. Also, perceived or explicated norms — such as community-created guidelines or terms of service — can influence what and how users post; for example politically conservative users being less open about their opinion on a platform they regard as unwelcoming of conservative statements, or strict moderation and banning being avoided by contributors through self-censoring. Similarly, perceived privacy risks can influence user behavior. A major challenge for digital trace-based studies is, therefore, disentangling what Ruths and Pfeffer call “platform-driven behavior” from behavior that would occur independently of the platform design and norms.

Evolving norms or technical settings may also affect the validity of longitudinal studies (Bruns and Weller, 2016) since these changes may cause “system drifts” as well as “behavioral drifts” (Salganik, 2017), contributing to reduced reliability of measurement over time (Lazer, 2015). Researchers should thoroughly investigate how particular plat-

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7For example, questions can be posed on topics for which there are more and less socially desirable responses and data collection modes can promote or inhibit accurate responding.

8Emerging, ideologically extreme platforms like Gab and Parler have the potential to lead to “migration” of whole user groups away from mainstream platforms, polarizing the platform landscape. (Ribeiro et al., 2020)
form affordances may affect their envisioned measurement.

| Example: Platform Affordances |
|------------------------------|
| Platform norms such as the character limit, platform design and features (e.g. display of trending topics or posts, feedback buttons) or terms of service and cultural norms can inhibit how and to what extent users express their opinion about the president, leading to platform affordances error. For example, users may have to write terse tweets or a thread consisting of multiple tweets to express their opinion on Twitter. Users may also be less likely to expose an opinion that they predict to be unpopular on the platform, for instance if platforms only allows positive feedback via like-buttons. |

**Platform Coverage Error.** The mismatch between the individuals in the target population and those being represented on the platform is the platform coverage error, a representation error. It is related to coverage error in the TSE, as the given sampling frame of a platform is generally not aligned with the target population (unless the platform itself is being studied). Further, different online platforms exhibit varying inclusion probabilities, as they attract specific audiences because of topical or technological idiosyncrasies (Smith, Anderson, and others, 2018). Twitter’s demographics, as a particular example, tend to be different from population demographics (Mislove et al., 2011), and Reddit users are predominantly young, Caucasian and male (Duggan and Smith, 2013). Population discrepancies could also arise due to differences in internet penetration or social media adoption rates in different socio-demographic or geographical groups, independent from the particular platform (Wang et al., 2019). The change of platforms’ user composition over time has additionally to be taken into account in terms of reliability of the study (Salganik, 2017).

Lastly, platform affordances also affect coverage: the inhibition of users’ traces to the point that they do not produce any relevant traces for the research in question effectively makes them “non-respondents”. This, for all intents and purposes, is indistinguishable from platform coverage error (Eckman and Kreuter, 2017).

| Example: Platform Coverage |
|---------------------------|
| Assume that full access to all relevant data on Twitter is given. Then, the sampling frame is restricted to users who have self-selected to register and to express their opinion on this specific social media platform. These respondents are likely not a representative sample of the target population (e.g., US voters) which causes a platform coverage error that |

A platform coverage error can be thought of as a counterpart to coverage error in the TSE. Researchers, as in survey methodology, may reweight participants by socio-demographics (directly available or inferred) to potentially obtain a representative sample (Pasek et al., 2018; Locker, 1993; An and Weber, 2015) (see Section 3.5), though the efficacy of these correction methods depends on the nature of the self-selection of users (Schnell, Noack, and Torregroza, 2017).

### 3.3 Data Collection

After choosing a platform, the next step of a digital trace based study consists of collecting data, e.g., through official APIs, web scraping, or collaborations with platform/data providers. Then, even if the full data of recorded traces is in principle available from the platform, researchers often select a subset of traces, users or both, by querying the data based on explicit features These can, for instance, include keywords or hashtags (O’Connor et al., 2010; Diaz et al., 2016; Stier et al., 2018), and for users, location or demographic markers, or their inclusion in lists (Chandrasekaran et al., 2017), see Table 1. This process is usually implemented (i) to discard traces (e.g., tweets) that are presumed to be irrelevant to the construct or (ii) to discard users (e.g., user profiles) that are unrelated to the elements in the target population. Additionally, if a researcher selects traces, they may have to collect supplementary information of the user leaving the trace (for example, profile and other posts of the user authoring the tweet) (Schober et al., 2016). We discuss researcher-controlled selection of traces and users below, and afterwards cover the case of provider-restricted data access.

**Trace Selection Error.** Typically, researcher-specified queries are used to capture traces broadly relevant to the construct of interest, to be possibly filtered further at later stages. These query choices determine on what basis the construct of interest is quantified and thus may lead to measurement errors. The difference between the ideal measurement and traces collected due to the researcher-specified query is termed trace selection error. The trace selection error is loosely related to measurement error in the TSE – the difference between the ideal, truthful answer to a question and the actual response obtained in a survey – in that traces might be included which do not truly carry information about the construct, or that informative ones might be missed. Low precision and low recall of queries may directly impact the measurement which can be established from the subselection of platform data used. He and Rothschild examine different methods of obtaining relevant political tweets, establishing that bias exists in keyword-based data collec-

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9 http://www.pewinternet.org/2018/03/01/social-media-use-in-2018/

10 Duplicate users for a member of the target population may also occur depending on the selected platform.

11 Not all “measurement errors”, but the specific “measurement error” box on the left side of Fig. 2
might be indirectly because they use different terms to refer to the president).

traces that are filtered out (e.g., teenagers may be excluded in the subset.

terest, their exclusion usually also removes those users that ing to their estimated ability to measure the construct of in-

Random Digit Generation where users are selected independently repeating the data selection step.

observation of relevant signals cannot be remedied without tion is finished (see Section “Data Preprocessing”), the non-

addressed in subsequent filtering steps after the data collec-

tidis, and Ipeirotis, 2014), and mitigate them via query ex-

precision and recall of the queries being used (Ruiz, Hris-

One may assess signal selection error through analysis of precision and recall of the queries being used (Ruiz, Hristidis, and Ipeirotis, 2014), and mitigate them via query ex-

pansion (Linder, 2017). While low precision can usually be addressed in subsequent filtering steps after the data collection is finished (see Section “Data Preprocessing”), the non-

observation of relevant signals cannot be remedied without repeating the data selection step.

User Selection Error. While traces are selected according to their estimated ability to measure the construct of interest, their exclusion usually also removes those users that produced them from the dataset (think of Twitter profiles attached to tweets), if no other traces of these users remain in the subset.\(^\text{12}\) In this manner, users with specific attributes might be indirectly excluded simply because they produce traces that are filtered out (e.g., teenagers may be excluded because they use different terms to refer to the president).

\(^{12}\)This is typically true for most data collection strategies except Random Digit Generation where users are selected independently of their characteristics.

The error incurred due to the gap between the selection of users and the sampling frame is called the user selection error. It is a representation error related, but distinct from, the sampling error in the TSE. It is also related to the coverage error if one considers the researcher-specified query result set as a second sampling frame,\(^{13}\) where user selection error is the gap between the sampling frame enforced by the query and the platform population. This error also occurs if users are directly excluded by their features (not via their traces); for instance, by removing user-profiles deemed irrelevant for inferences to the target population as determined by their indicated location, age or (non-)placement on a user list. This is especially critical since the voluntary self-

reporting of such attributes differs between certain groups of users, such as certain demographics being less prone to reveal their location or gender in their account information or posts (Pavalanathan and Eisenstein, 2015), and additionally can be unreliable due to their variation over time (Salganik, 2017).

There are many approaches to collecting data for both traces and users (cf. Table 1) and each comes with different types of trace and user selection pitfalls. As keyword-based search is a popular choice, Tufekci analyzed how hashtags can be used for data collection on Twitter and finds that hashtag usage tapers down as time goes on – users continue to discuss a certain topic, they merely stop using pertinent hashtags (Tufekci, 2014). For collecting data related to elections or political opinion, many studies use mentions of the political candidates to collect data related to them (Barberá, 2016; O’Connor et al., 2010; Diaz et al., 2016; Stier et al., 2018). While this a high-precision query, it may have low recall, excluding users who refer to political candidates with nicknames, thereby reducing the sample’s generalizability. On the other hand, it may also include ineligible users who might have been referring to someone with the same name as the politician, in case a candidate’s name is common.

In addition to keyword selection, other sources for data se-

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**Table 1: Different types of feature-based data collection strategies, their explanation and example.**

| Query Type          | Definition                                                                 | Examples of Research Question                                                                 |
|---------------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Keyword             | Using keywords including terms, hashtags, image tags regular expressions to subset traces such as posts (tweets, comments, images) or users (users) | Predicting Influenza rates from search queries (Yuan et al., 2013)                              |
|                     |                                                                          | Understanding the use and effect of psychiatric drugs through Twitter (Buntain and Golbeck, 2015) |
| Attribute           | Using attributes such as location or community affiliation to subset users such as users who may have the relevant attribute in their biography | Inferring demographic information through mobility patterns on photosharing platforms (Riederer et al., 2015) |
|                     |                                                                          | Geographic Panels used to study responses to mass shootings and TV advertising (Zhang, Hill, and Rothschild, 2016) |
| Random Digit        | Generating random digits and using them as identifiers of platform users | Studying collective privacy behaviour of users (Garcia et al., 2018)                              |
| Generation          |                                                                          | Understanding the demographics and voting behaviour of Twitter users (Barberá, 2016)             |
| Structure           | Using structural properties of users or traces to select data such as interactions (retweeting, liking, friending) | Understanding the influence of users (Cha et al., 2010)                                          |
|                     |                                                                          | Predicting political affinity of Twitter users based on their mention networks (Conover et al., 2011) |
lection are also in use, e.g., those based on attributes, such as location (Bruns and Stieglitz, 2014) or structural characteristics (Demartini, 2007) or affiliation to particular sub-communities or lists (Chandrasekharan et al., 2017), and random digit generation (RDG) (Barberá, 2016). Each method has different strengths and weaknesses, with random digit generation (RDG) being closest to the Random Digit Dialing method of conducting surveys, although the method may generate a very small sample of relevant tweets (Barberá, 2016). Lists of users as well as selection based on reported attributes also restrict the dataset to users who have either chosen to be marked by them, have been marked by others, often leading to additional coverage error since the characteristics of selected users may be systematically different from the target population (Cohen and Ruths, 2013). Further, when network data is collected, different crawling and sampling strategies may impact the accuracy of various global and local statistical network measures such as centrality or degree (Galaskiewicz, 1991; Borgatti, Carley, and Krackhardt, 2006; Kossinets, 2006; Wang et al., 2012; Lee and Pfeffer, 2015; Costenbader and Valente, 2003), the representation of minorities and majorities in the sample network (Wagner et al., 2017) and the estimation of dynamic processes such as peer effects in networks (Yang, Ribeiro, and Neville, 2017). This is especially important if the construct of interest is operationalized with structural measurements (e.g., if political leaning is assessed based on the connectivity between users and politicians or if extroversion is assessed based on the number of interaction partners).

Additionally, data access restrictions by platform providers can aggravate trace and user selection errors. Many platforms regulate data access to a provider-determined subset that may not be a probabilistic sample of the whole set of traces in their system – inducing a representation error, but in this instance regarding the platform population. Such an artificial restriction can indeed be closely linked to sampling error in the TSE, since a nonprobabilistic sample is drawn from the platform, though not by the researcher. For example, while for some platforms like Github or Stack Exchange, the entire history of traces ever generated are available and the researcher can make selections from this full set freely, others like Facebook Ads or Google Trends only share aggregated traces. As the most prominent example, Twitter provides data consumers with varying level of access. A popular choice of obtaining Twitter data is through the 1% ‘spritzer’ API, yet research has found that the free 1% sample is significantly different from the commercial 10% ‘gardenhose’ API (Morstatter et al., 2013). One reason for a misrepresentation of users is overly active users being assigned a higher inclusion probability than others in such a sample, simply because they produce more traces and sampling is done over traces in a given time frame (Schober et al., 2016).

Both platforms and researchers may also decide to limit what data can be collected based in order to protect user privacy.15

| Example: User Selection |
|-------------------------|
| When studying political opinions on Twitter, vocal or opinionated individuals’ opinions will be overrepresented, especially when data is collected based on traces (e.g., tweets), instead of individual accounts (e.g., tweets stratified by account activity) (Barberá, 2016; O’Connor et al., 2010; Pasek et al., 2018; Diaz et al., 2016) simply because they tweet more about the topic and have a higher probability of being included in the sample than others. Further, certain groups of users (e.g., teenagers or Spanish speaking people living in the US) may be underrepresented if keyword lists are generated that mainly capture how adult Americans talk about politics. |

3.4 Data Preprocessing

Data preprocessing refers to the process of removing noise in the form of ineligible traces and users from the raw dataset as well as augmenting it with extraneous information or additionally needed meta-data.

Trace Preprocessing Trace preprocessing is done since researchers may want additional information about traces or may want to discard ineligible traces that have been mistakenly included due to data collection. The reduction or augmentation of traces, while aimed at improving our ability to measure the construct through them, may also further distort them.

Trace Augmentation Error. The augmentation of traces can comprise several means: sentiment detection, named entity recognition, or stance detection on the text content of a post; the annotation of “like” actions with receiver and sender information; or the annotation of image material with objects recognized within. This augmentation is done as part of measuring the theoretical construct and, due to the size and nature of the data, mainly pertains to the machine-reliant coding of content. An error may be introduced in this step due to false positives and negatives of the annotation method. Just as answers to open-ended questions in a survey are coded to ascertain categories and inadequately trained coders can assign incorrect labels, trace augmentation error occurs often due to inaccurate categorization due to the usage of pretrained ML methods or other pre-defined heuristics, frequently designed for different contexts. Particularly the annotation of natural language texts has been popular in digital trace studies and even though a large body of research has emerged on natural language processing methods, many challenges remain (Puschmann and Powell, 2018), including a lack of algorithmic interpretability for complex or black-box models. Study designers need to carefully assess the

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14Recent changes to Twitter’s ID generation mechanism renders the RDG data collection method no longer viable: https://developer.twitter.com/en/docs/basics/twitter-ids

15Platforms deal with content deletion by users in different ways, which can also affect the resultant subsets, a point we hope to explore in future work.
context for which an annotation method was built before applying it and consult benchmarking studies for commonly used methods (González-Bailón and Paltoglou, 2015). In case methods have been developed for a different type of content, domain adaptation may also be used to improve the performance of methods trained on a data source different from the current data of interest (Hamilton et al., 2016).

**Trace Reduction Error.** Finally, certain traces may be ineligible items for a variety of reasons such as spam, hashtag hijacking or because they are irrelevant to the task at hand. The error incurred due to the removal of ineligible traces is termed the trace reduction error. Researchers should investigate precision and recall of methods that remove irrelevant traces to estimate the trace reduction error (Kumar and Shah, 2018).

**Example: Trace Preprocessing**

**Augmentation:** Political tweets are often annotated with sentiment to understand public opinion (O’Connor et al., 2010; Barberá, 2016). However, the users of different social media platforms might use different vocabularies (e.g., “Web-born” slang and abbreviations) than those covered in popular sentiment lexicons and even use words in different contexts, leading to misidentification or under-coverage of sentiment for a certain platform or sub-community on that platform (Hamilton et al., 2016).

**Reduction:** Researchers might decide to use a classifier that removes spam, but has a high false positive rate, inadvertently removing non-spam tweets. They might likewise discard tweets without textual content, thereby ignoring relevant statements made through hyperlinks or embedded pictures/videos.

**User Preprocessing** In analogy to reducing or augmenting traces, users may also be preprocessed. In this step, the digital representations of humans, such as profiles, are augmented with auxiliary information and/or certain users are removed because they were ineligible units mistakenly included in the sampling frame. These preprocessing steps can affect the representativeness of the final data used for analysis.

**User Augmentation Error.** Researchers might be interested in additional attributes of the users in the data sample, which may serve as dependent independent variables in their analysis; for example, a research might be interested in how political leaning affects the propensity to spread misinformation. Additional user attributes are generally also of interest for reweighting digital trace data by socio-demographic attributes and/or by activity levels of individuals. The former is traditionally also done in surveys to mitigate representation errors (discussed as ‘Adjustment’ in Section “Analysis and Inference”).

However, since such attributes are rarely pre-collected and/or available in platform data, demographic attribute inference for accounts of individuals is a popular way to achieve such a task, often with the help of machine learning methods (Zhang et al., 2016; Rao et al., 2010; Sap et al., 2014; Wang et al., 2019). Of course, demographic attribute inference itself is a task that may be affected by various errors (Karimi et al., 2016; McCormick et al., 2017) and can be especially problematic if there are different error rates for different groups of people (Buolamwini and Gebru, 2018). Furthermore, these automated methods are often underspecified, operating on a limited understanding of social categories such as gender (Scheuerman, Paul, and Brubaker, 2019) which often excludes transgender and gender non-binary people (Hamidi, Scheuerman, and Branham, 2018). There are other crucial departures from survey research in gender attribution— automated methods (mis)gender people at scale and without their consent (Keyes, 2018), whereas demographic attributes are self-reported in surveys. Similar tensions apply to inferring race (Khan and Fu, 2021). Such automated approaches for classifying users according to (perceived) characteristics thus have a strong ethical component, as they might harm marginalized communities by more frequently misclassifying minorities (Buolamwini and Gebru, 2018).

Platforms may also offer aggregate information about their user base, which can potentially be supplied through provider-internal inference methods and be prone to the same kind of errors without the researcher knowing (Zagheni, Weber, and Gummadi, 2017). Besides demographic features calculated network position of the account on the platform, or linking to corresponding accounts on other platforms also constitute user augmentation.

The overall error incurred due to the efficacy of user augmentation methods is denoted as user augmentation error.

**User Reduction Error.** In addition to user augmentation, preprocessing steps usually followed in the literature include removing inactive users, spam users, and non-human users— comparable to “ineligible units” in survey terminology— or filter content based on various observed or inferred criteria (e.g., location of a tweet, the topic of a message). Similar to user augmentation error, the methods for detecting and removing specific type of users are usually not perfect and the performance may depend on the characteristics of the data (cf. (De Cristofaro et al., 2018) and (Wu et al., 2018)). Therefore it is important that researchers analyze the accuracy of the selected reduction method to estimate the user reduction error.

**Example: User Preprocessing**

**Augmentation:** Twitter users’ gender, ethnicity, or location may be inferred to understand how presidential approval differs across demographic groups. Yet, automated gender inference methods based on images have higher error rates for African Americans than White Americans (Buolamwini and Gebru, 2018); therefore, gender inferred through such means may inaccurately estimate approval rates among African American males versus females compared to their White counterparts, which raises serious ethical concerns.
3.5 Analysis and Inference

After preprocessing the dataset, an estimate is calculated for the construct in the target population.

**Trace Measurement Error.**

In this step, a concrete measurement of the construct is calculated—say, a [0,1] value of presidential approval from a vector of sentiment scores associated with a tweet—and models are built that link this measurement to other variables. It is therefore distinct to trace augmentation, where traces are annotated with auxiliary information to measure the construct (parts-of-speech tags, sentiment, etc.). In practice, these steps can be highly intertwined, but it is still useful to conceptually disentangle them as separate stages.

The researcher can calculate the final estimate through many different techniques, from simple counting and heuristics to complex ML models. While simpler methods may be less powerful, they are often more interpretable and less computationally intensive. On top of errors incurred in previous stages (e.g., not all dimensions of the construct captured during data collection), the model used might only detect certain aspects of the construct or on spurious artifacts of the data being analyzed. For example, a ML model spotting sexist attitudes may work well for detecting obviously hostile attacks based on gender identity but fail to capture benevolent sexism, though they are both dimensions of the construct of sexism (Jha and Mamidi, 2017; Samory et al., 2021). Even if the technique is developed or trained for the specific data collected, it can therefore still suffer from low validity. Any error that distorts how the construct is estimated due to modeling choices is denoted as **trace measurement error**. Even if validity is high for the given study, a replication of the measurement model on a different dataset—a future collection of the same platform data or a completely different dataset—can fail, i.e., have low reliability (Conrad et al., 2019; Sen, Flöck, and Wagner, 2020). Different kinds of traces can be taken into account to different degrees in the final estimate, e.g., in order to account for differences in activity of the users generating the traces (e.g., power users’ posts) or their relevance to the construct to be measured. This can lead to erroneous final estimates, which we denote as **trace measurement error**. This error may arise due to the choice of modeling or aggregation methods used by the researcher as well as how the traces are mapped to the users.

Researchers should also account for heterogeneity since digital traces are generated by various subgroups of users who may have different behavior. Aggregation may mask or even reverse underlying trends of digital traces due to trace measurement errors in the form of Simpson’s paradoxes (a type of ecological fallacy) (Alipourfard, Fennell, and Lerman, 2018; Howison, Wiggins, and Crowston, 2011; Lerman, 2018)). Further, the performance of machine learning methods will be impacted by this heterogeneity and the performance of a model can differ enormously across different subgroups of users especially if some groups are much larger and/or much more active (i.e. produce more traces that can be used for training).

Trace measurement error has been addressed in related work as well, under different names and to different degrees. For example, Amaya, Biemer, and Kinyon (2020) as well as West, Sakshaug, and Kim (2017) introduce another error, called **analytic error**, which West, Sakshaug, and Kim (2017) characterize as “important but understudied aspect of the total survey error (TSE) paradigm”. Following Amaya, Biemer, and Kinyon (2020), analytic error is broadly related to all errors made by researchers when analyzing the data and interpreting the results, especially when applying automated analytic methods. A consequence of analytic error can be false conclusions and incorrect models, which manifests in multiple ways (e.g., spurious correlations, endogeneity, causation versus causality) (Baker, 2017). In that sense, the equivalent of one component of analytic errors, i.e., errors incurred due to the choice of modeling techniques, is the trace measurement error. The other component, errors due to choice of survey weights, is described below in adjustment error and is related to analytic error in the sense of West, Sakshaug, and Kim (2017); in addition, they put special emphasis on applying appropriate estimation methods when analyzing complex samples—e.g., using proper variance estimation methods.

**Example: Trace Measurement**

Depending on the way the construct was defined (say, positive sentiment towards the president), and trace augmentation performance (lexicons which count words with a sentiment polarity), the researcher obtains tweets whose positive and negative words have been counted. Now the researcher may define a final link function which combines all traces into a single aggregate for the construct of “approval”. She may choose to count the normalized positive words in a day (Barberá, 2016), the ratio of positive and negative words per tweet or add all the ratio of all tweets in a day (Pasek et al., 2019). The former calculation of counting positive words in a day may underestimate negative sentiments of a particular day, while in the latter aggregate, negative and positive stances in tweets which report both would neutralize each other, resulting in the tweet having no sentiment.

A user may have expressed varying sentiments in multiple tweets. The researcher faces the choice of averaging the sentiment across all tweets, taking the most frequently expressed sentiment or not aggre-
gating them at all and (implicitly) assuming each tweet to be a trace of an individual user (Tumasjan et al., 2010; O’Connor et al., 2010; Barberá, 2016) which may amplify some users’ voices at the cost of others.

Either to avoid the vocabulary mismatch between pre-defined sentiment lexica and social media language or because sentiment is an inadequate proxy for approval, researchers may alternatively want to use machine learning methods that learn which words indicate approval towards the president by looking at extreme cases (e.g., tweets about the president from his supporters and critics). The validity of this measurement depends on the data it is trained on and to what extent this data is representative of the population and the construct. That means the researchers have to show that the selected supporters and critics expose approval or disapproval towards the president in a similar way as random users (Cohen and Ruths, 2013).

### Adjustment Error

To infer to the target population, researchers can attempt to account for platform coverage error (possibly aggravated by user selection or preprocessing). Thus, they may use techniques leveraged to reduce bias when estimating population parameters employing non-probabilistic samples, such as opt-in web surveys (Goel, Obeng, and Rothschild, 2015, 2017). Researchers have suggested specific ways to handle the non-probabilistic nature of these surveys, which may also be applied to digital traces (Kohler, 2019; Kohler, Kreuter, and Stuart, 2019). In contrast to Kohler (2019) or Kohler, Kreuter, and Stuart (2019), some researchers suggest weighting techniques like raking or post-stratification to correct for coverage and sampling errors. The availability of demographic information—a or other features applicable for adjustment—as well as the choice of method can both cause errors which we label adjustment error, in line with Groves et al. (2009). It should be noted that corrections solely based on socio-demographic attributes are not a panacea to solve coverage or non-response issues (Schnell, Noack, and Torregroza, 2017).

Reweighting has been explored in studies using digital traces (Zagheni and Weber, 2015; Barberá, 2016; Pasek et al., 2018, 2019; Wang et al., 2019) using calibration or post-stratification. Unlike in survey methodology where scholarship has systematically studied which approaches work well for which type of data sources (Cornesse et al., 2020; Kohler, 2019; Kohler, Kreuter, and Stuart, 2019; Cornesse and Blom, 2020), there is a lack of comprehensive study regarding reweighting in digital traces. Broadly, there are two approaches to reweighting in digital trace based studies. The first approach reweights the data sample according to a known population, for example obtained through the census distribution (Yildiz et al., 2017; Zagheni and Weber, 2015). The second approach reweights general population surveys according to the demographic distribution of the online platform itself (Pasek et al., 2018, 2019) – found through, e.g., usage surveys or provided by the platform itself. While the second method has the advantage of bypassing the use of biased methods for demographic inference (thus mitigating user augmentation errors), the platform demographics might not apply to the particular dataset since all users are not equally active on all topics and the error introduced by this reweighting step is difficult to quantify. For the first method, while researchers often use biased methods for demographic inference, the errors of these methods can be quantified through error analysis.

### Example: Adjustment

When comparing presidential approval on Twitter with survey data, Pasek et al. (2019) reweight the survey estimates with Twitter usage demographics but fail to find alignment between the two measures. In this case, the researchers assume that the demographics of Twitter users is the same as for a subset of Twitter users tweeting about the president, an assumption which might not be true. Previous research has shown that users who talk about politics on Twitter tend to have different characteristics than random Twitter users (Cohen and Ruths, 2013) and that they tend to be younger and have a higher chance of being white men (Bekafigo and McBride, 2013). Therefore using Twitter demographics as a proxy for politically vocal Twitter users may lead to adjustment errors.

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4 Application of the Error Framework

To illustrate the applicability and the utility of the framework, we will now look at typical computational social science studies through the lens of our error framework. We note that the point of this section is not to criticize the design choices of the researchers conducting these respective studies, but rather to systematically highlight the errors that can lurk in various steps, most of which the authors have thought about themselves and have applied mitigation approaches to. No study is without limitations, and some errors simply cannot be fully mitigated with current techniques (such as imperfect demographic inference). In that vein, a central aim of our error framework is to systematically describe and document the errors that may occur when designing and conducting digital trace based studies using a vocabulary that enables the communication across disciplines.

4.1 Case Study: Assessing County Health via Twitter

The first case study we explore is Culotta’s endeavour to infer multiple county-level health statistics (e.g., obesity, diabetes, access to healthy foods) based on tweets originating in those counties (Culotta, 2014). The author collects tweets which include platform-generated geocodes of 100
American counties, analyzes the content of the tweets using lexicons to infer health-related traces, and finally aggregates them by county. The author also annotates the demographics of the Twitter users and reweights the estimates according to the county statistics to reduce the representation bias of Twitter. In the following section, we outline the different errors possibly occurring in each stage of this study.

Construct Definition and Target Population

Constructs: 27 county-level health statistics (e.g., obesity, diabetes, access to healthy foods, teen birth rates) are the constructs to be quantified and the ideal measurement envisioned is tweets related to these health issues.

Target population: the population of the 100 most populous counties in the USA.

Issues of Validity: it is unclear if and how people reveal health-related issues on Twitter. Some health-related issues may be more sensitive than others, therefore Twitter users may be less likely to publicly disclose them. Further, it is possible that only certain type of Twitter users reveal health-related issues. Lastly, the act of mentioning an issue is not clearly conceptually linked to either experiencing, observing or simply thinking about it.

Platform Selection

Sampling frame: Twitter accounts and their tweets

Platform Affordances Error: Twitter’s formatting guidelines (140 character limit at the time of the study), allowances (use of hashtags, links, or mentions) and content sharing restrictions directly impact how users tweet about health and might limit the expressivity of posts talking about the constructs at hand.

Platform Coverage Error: Twitter’s skewed demographics present a recurrent problem prone to causing platform coverage error, since the platform population deviates from the target population. The author strives to adjust for this coverage mismatch through reweighting which we discuss below.

Data Collection

The author chooses an attribute-based and trace-based data collection strategy where the attribute of interest is location. Specifically, all tweets corresponding to US county geolocations are collected. The profile information of the authors of the health-related tweets is also collected.

Traces: Tweets

Trace Selection Error: Using geolocations to select tweets leads to certain issues on the trace level: (1) Tweets from within the county about the health issues of interest might not be geocoded and therefore not selected, and (2) some tweets might not reflect conditions in the specific county since they are emitted by users not residing there.

Users: Twitter accounts

User Selection Error: Firstly, the above-mentioned trace selection error of course is directly reflected in the erroneous inclusion of accounts of individuals who are physically in the county at the time of tweeting but do not reside there permanently. Secondly, not all residents who are twitter users use geocodes; in fact, only a part of all users does, which are in turn not representative of the Twitter user population (Pavalanathan and Eisenstein, 2015).

Data Preprocessing

To quantify health-related traces in the tweets, the author uses two lexicons – LIWC and PERMA – to annotate various linguistic, psychological, social and emotional aspects of the tweets as well as the profile descriptions of the tweet authors. Preprocessing steps also include the use of automatic demographic inference for augmenting gender and ethnicity (race) information of the authors of the health-related tweets.

Trace Augmentation Error: Occurs due to shortcomings of lexicon-based approaches. Lexicons are often not designed for social media terminology (such as hashtags) and may therefore suffer from low precision and recall when annotating a tweet with a concept/construct or auxiliary features to measure the construct.

User Augmentation Error: The methods used for demographic inference are likely to introduce at least some inaccuracies, particularly if they are based on a gold standard dataset that does not align completely with the characteristics of the annotated data.

User Reduction Error: Users for whom demographics cannot be inferred are not included in the analysis. These accounts might systematically be from a certain demographic stratum, e.g., females or older individuals.

Data Analysis

Finally, the author aggregates the lexica-annotated tweets and user descriptions by county. He also applies reweighting to address the coverage mismatch of Twitter users and the target population.

Trace Measurement Error: The author notes that if certain users are more active than others, their health traces will be weighted accordingly. Therefore, he normalizes by users, mitigating trace measurement error.

Adjustment errors: The choice of method as well as the variables used for reweighting may lead to adjustment errors. For example, gender and ethnicity may not be sufficient attributes to explain the self-selection bias of Twitter users. Furthermore, the coverage bias induced by selecting only those users who have enabled geotagging, is not addressed.
4.2 Case Study: Nowcasting Flu Activity through Wikipedia Views

Our second case study focuses on predicting the prevalence of Influenza-like Illnesses (ILI) from Wikipedia usage by McIver and Brownstein (2014), which stands as an illustrative example for a line of research on predictions based on digital trace data that is based on aggregated traces. Traditionally, cases of ILI in the US would be measured by reports from local medical professionals, and then be recorded by a central agency like the Center for Disease Control and Prevention (CDC). The authors investigate whether Wikipedia usage rates would be an adequate replacement for reports by the CDC. Specifically, the authors use views on selected Wikipedia articles relevant to ILI topics to predict ILI prevalence.

Construct Definition and Target Population

Construct: A case of ILI of a person as diagnosed by the CDC.

Target Population: Described to be the "American Population", which could refer to all U.S. citizens residing in the U.S., all U.S. residents or simply the same population for which CDC data is collected that is used as the gold standard set.

Issues of Validity: What does the act of accessing ILI-related Wikipedia pages imply about the person who looks at these pages? Do we assume that these persons suffer from influenza or related symptoms themselves, or could this also be individuals with a general interest in learning about the disease, potentially also inspired by media coverage of a related topic? Given that we do assume the majority of readers of ILI-related articles on Wikipedia to be infected or at least affected individuals: feeling sick does not necessarily imply that a viewer contracted an ILI and not another illness. Only a medical expert can discern ILI-symptoms from similar diseases. To test validity in such cases, one option would be to survey a random sample of Wikipedia readers that land on the selected ILI-related articles to find out about their health status or alternative motivations. Further surveys and/or focus groups could help to learn about if, how, and where people search for advice online when being sick.

Platform Selection

Sampling frame: Wikipedia pageviews. The researcher has no access to accounts linked to pageviews and can therefore only select a data subset on the trace level.

Platform Affordances Error: The way users arrive at and interact with the articles presented, thereby affecting viewing behavior, is shaped by Wikipedia’s interface layout, the inter-article link structure and external search results linking into this structure. I.e., users are frequently arriving at Wikipedia articles from a Google search (McMahon, Johnson, and Hecht, 2017; Dimitrov et al., 2019) implying that Google’s ranking of Wikipedia’s ILI-related articles with respect to certain search queries impacts the digital traces we observe in Wikipedia data as well. Past research has also found that article structure and the position of links play an important role in the navigation habits of users (Lamprecht et al., 2017).

Platform Coverage Error: The readers of Wikipedia are not representative of the target population.

Data Collection

The authors of the paper curate a list of 32 Wikipedia articles that they identified to be relevant for ILI, including Avian influenza, Influenza Virus B, Centers for Disease Control and Prevention, Common Cold, Vaccine, Influenza.

Traces: Hourly aggregated article views of 32 selected articles, obtained from http://stats.grok.se (which is no longer operable).

Trace Selection Error: The views for certain selected articles might not indicate a strong primary interest in ILI (‘Centers for Disease Control and Prevention’, ‘Vaccine’ are viewed for many other reasons). Other relevant articles’ views are not counted – “influenza vaccine”, for example, seems relevant but is not included.

Users: Not observable. Could be assumed to be single browser agents connecting to the server and visiting pages. Each session is an anonymous or a logged in user; however, these are not made available publicly by Wikimedia.

User Selection Error: Assuming that the selected articles might in fact be primarily viewed out of interest in ILI, there remains another potential error source: Different subgroups of the target population (e.g., medically trained individuals) might turn to different articles for their information needs about ILI that are not included in the 32 selected pages (e.g. articles with technical titles). As these traces are excluded, so are these members of the target population.

A detailed explanation for the selection criteria of the particular set of Wikipedia articles would be useful for comparing the results with related approaches. For example, it could be mentioned if the selection process was informed by specific theory or by empirical findings from interviews or focus groups. Such information would help to assess the impact of trace selection errors. Another thing to keep in mind is the aspect of time, since existing articles may change, new articles may be added during the field observation, leading to unstable estimates.

Data Analysis

Finally, weekly flu rates are estimated using a Generalised Linear Model (GLM) on the article views. The authors’ outcome variable is the proportion of positive age-weighted CDC ILI activity and the 35 predictor variables include the views on the 32 ILI-related articles, year and month. It is assumed that the GLM learns how ILI occurrences fluctuate based on the changes in the article views.

Trace Measurement Errors: Aggregated traces cannot be matched to users that produced them. It is, therefore, difficult to identify if multiple traces are referring to the same user (multiple views of ILI-related Wikipedia pages made by the
same person). As such, views of power users of Wikipedia are counted much more often than the average readers’.

5 Related Work

Our error framework for digital traces is inspired by insights from two disciplines: those that have been developed and refined for decades in (i) survey methodology as well as insights from the relatively new but rapidly developing field of (ii) computational social science, which has increasingly sought to understand the uses of newer forms data developed in the digital age. In this section, we discuss some of the main threads of research spanning these fields.

Survey Methods. The Total Survey Error Framework is an amalgamation of efforts to consolidate the different errors in the survey pipeline (Groves and Lyberg, 2010; Biemer and Christ, 2008). Recently, researchers have tried to explore the efficacy of non-probability sampled surveys such as opt-in web surveys (Goel, Obeng, and Rothschild, 2015, 2017), where they find that adjustment methods can improve estimates even if there are representation errors. On a similar vein, Kohler, Kreuter, and Stuart (2019) find that nonprobability samples can be effective in certain cases. Meng (2018) poses the question “Which one should we trust more, a 5% survey sample or an 80% administrative dataset?” and introduces the concept of the ‘data defect index’ to make surveys more comparable. Researchers have also attempted to integrate survey data and digital traces to analyze and uncover social scientific questions (Stier et al., 2019).

The Potentials of Digital Traces. Web and social media data has been leveraged to ‘predict the future’ in many areas such as politics, health, and economics (Aksitás and Zimmermann, 2015; Phillips et al., 2017). It is also considered as a means for learning about the present, e.g., for gaining insights into human behavior and opinions, such as using search queries to examine agenda-setting effects (Ripberger, 2011), leveraging Instagram to detect drug use (Yang and Luo, 2017), and measure consumer confidence through Twitter (Pasek et al., 2018). Acknowledging the potential advantages of digital trace data, the American Association for Public Opinion Research (AAPOR) has commissioned reports to understand the feasibility of using digital trace data for public opinion research (Japec et al., 2015; Murphy and others, 2018).

The Pitfalls of Digital Traces. There is some important work aimed at uncovering errors that arise from using online data or, more generally, various kinds of digital trace data. Recently, researchers have studied the pitfalls related to political science research using digital trace data (Gayo-Avello, 2012; Metaxas, Mustafaraj, and Gayo-Avello, 2011; Diaz et al., 2016), with Jungherr et al. (2017); Bender et al. (2021), especially focusing on issues of validity. Researchers have also analyzed biases in digital traces arising due to demographic differences (Pavalanathan and Eisenstein, 2015; Olteanu, Weber, and Gatica-Perez, 2016), platform effects (Malik and Pfeffer, 2016) and data availability (Morrstatter et al., 2013; Pfeffer, Mayer, and Morstatter, 2018). More generally, Olteanu et al. (2019), provide a comprehensive overview of the errors and biases that could potentially affect studies based on digital behavioral data as well as outlining the errors in an idealized study framework, while Tufekci (2014) outlines errors that can occur in Twitter-based studies. Recently Jungherr (2017) calls for conceptualizing a measurement theory that may adequately account for the pitfalls of digital traces.

Addressing and Documenting the Pitfalls of Digital Traces. Recently, researchers working with digital traces have used techniques typically used in surveys, to correct representation errors (Zagheni, Weber, and Gummadi, 2017; Fatehkia, Kashyap, and Weber, 2018; Wang et al., 2019). Besides, addressing specific biases, researchers have also attempted to identify and document the different errors in digital traces as a first step to addressing them. In addition to an overview of biases in digital trace data, Olteanu et al. provide a framework using an idealized pipeline to enumerate various errors and how they may arise (Olteanu et al., 2019). While highly comprehensive, they do not establish a connection with the Total Survey Error framework (Groves and Lyberg, 2010), despite the similarities of errors that plague surveys as well. Ruths and Pfeffer prescribe actions that researchers can follow to reduce errors in social media data to two steps: data collection and methods (Ruths and Pfeffer, 2014). We extend this work in two ways: (1) by expanding our understanding of errors beyond social media platforms to other forms of digital trace data and (2) by taking a deep dive at more fine-grained steps to understand which design decision by a researcher contributes to what kind of error.

Hsieh and Murphy (2017) conceptualize the Total Twitter Error (TTE) Framework where they describe three kinds of errors in studying unstructured Twitter textual data, which can be mapped to survey errors: coverage error, query error and interpretation error. The authors also provide an empirical study of inferring attitudes towards political issues from tweets and limit their error framework to studies which follow a similar lifecycle. We aim to extend this framework to more diverse inference strategies, beyond textual analysis as well as for social media platforms other than Twitter and other forms of digital trace data.

The AAPOR report on public opinion assessment from ‘Big Data’ sources (which includes large data sources other than digital trace data such as traffic and infrastructure data) describes a way to extend the TSE to such data, but cautions that a potential framework will have to account for errors that are specific to big data (Japec et al., 2015). We restrict our error framework to digital trace data from the web which are collected based on a typical social sensing study pipeline, highlight where and how some of the new types of errors may arise, and how researchers may tackle them. Recent efforts to document issues in using digital trace data include “Datasets for Datasets”, proposed by Gebru et al. (2018) where datasets are accompanied with a datasheet that contains its motivation, composition, collection process, recommended uses as well as ‘Model cards’ which document the use cases for machine learning models (Mitchell et al., 2019). We propose a similar strategy to document digital trace based research designs to enable better communication, transparency, reproducibility, and reuse of said data.

Closest to our work is Amaya, Biemer, and Kinyon
improving estimates from human digital traces online since it allows us to transparently document errors. Future work will hopefully build on and extend the foundation laid by TED-On to effectively quantify and mitigate errors inherent to digital trace data.

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