Advancing Perspectivist Ground Truthing with Social Science

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# Introduction

AI systems run on data. Data are used to ‘train’ *models* - imperfect, simplified mathematical or computational representations of a phenomenon or process in the real world [[1]](#footnote-20). Where an AI system is a complete application with integrated components e.g. an interface, programmatic logic, and one or more models aimed at performing tasks typically requiring human intelligence[[2]](#footnote-21), the models themselves are embedded components that take inputs (e.g. media like text, images, audio, or data) and produce outputs (e.g. classifications, predictions or some form of decision). Model *behavior* - the model’s output or response to a given input - is determined by their *parameters* - internal settings or values[[3]](#footnote-22). *Algorithms* - step by step instructions, executed in order[[4]](#footnote-23) - are used to estimate model parameters from the ‘training’ data. As models used in AI systems are designed to perform tasks, their performance is often evaluated empirically by comparing their outputs to a reference. This reference is often a second form of data, referred to as the ‘ground truth’ or ‘gold standard’, which represents the ideal expected output of the system.

Training data may be tabular data, but is often a form of media - text, audio, images, or video, whereas reference data often contains aggregated input from humans (Geiger et al., 2020, 2021; Muller et al., 2021; Sav et al., 2023). Data sets designed for training, reference or both, are often re-used, likely due to the ease of access - often a mere download - compared to the effort and cost required to design, collect, and evaluate such data sets. Human input may be collected explicitly - where a phenomenon of interest is set as a target, and humans are given a task whereby their responses produce data relevant to the target. Common scenarios include human judges annotating, labeling, or rating a) individual pieces of content of the same form as the training data, or b) generated system outputs for the presence/absence, or degree of the phenomenon of interest(Muller et al., 2021). Data may also be collected implicitly - where digital traces of human behavior, e.g. media consumption, form the target (Sav et al., 2023).

Qualities of both forms of data (training and evaluation) determine the quality of the system, whether used to train the system, to evaluate it, or both. Parameters are estimated from the training data, with the aim that observable patterns will be recognized in the data, and affect the behavior of the model used by the system. Thus, if the model accurately reflects the data, parameters will accurately reflect imperfections, inaccuracies, biases etc. in the data as well. Also, as models are evaluated by comparing their outputs to reference data, such that preferred models are those whose outputs most closely resemble the reference data (Birhane et al., 2022), imperfections in the reference are reflected in the models preferred. Thus, the best possible performance in the real world directly corresponds to the degree to which training and reference data represent the phenomenon of interest, in the environment to which it is to be deployed. Thus, evaluating a model in an AI system involves two measurement problems: 1) measuring the phenomenon of interest in the media selected for inclusion in the reference and/or training data, and 2) measuring the similarity of the output of a model to the reference (Welty et al., 2019). While the second has received extensive attention, the first has not.

Human input is never identical even when submitted carefully - in other words, people do not perfectly agree (Cabitza et al., 2023). As most models are only compatible with a single reference point per piece of content, multiple inputs are often collected from different people with reference to items of content, and subsequently aggregated. This ignores the process that produced the reference data by assuming a singular ‘ground truth’ per piece of content and treating all disagreement as ‘noise’ rather than ‘signal’, leading to biased or inaccurate reference data (Aroyo & Welty, 2015; Cabitza et al., 2023). Thus, relevant distributions in the data used as the reference and/or training must resemble those in the environment to which the system will be deployed (Hullman et al., 2022), but also account for the fact that human input is never identical (Aroyo & Welty, 2015; Cabitza et al., 2023).

Although the true values of the relevant distributions are unknowable, cues to whether human input resembles useful measurements can be calculated (Jacobs & Wallach, 2021; Welty et al., 2019), and can account for a range of reasonable interpretations in the reference (Aroyo & Welty, 2015; Cabitza et al., 2023). The social sciences have developed sampling methods to represent distributions in populations which can be adapted to the collection of content (Groves et al., 2009), and syntheses show how to leverage variance in human input using knowledge from survey science (Beck et al., 2022), metrology (Welty et al., 2019), psychometrics (Jacobs & Wallach, 2021), and the perspective approach to ground-truthing (Cabitza et al., 2023). Yet, knowledge from these fields has broadly not been applied in the field of Machine Learning, leading to issues of representation and measurement (Hullman et al., 2022).

## Present Work

Present work firstly attempts to synthesize input from various fields on how to better gather reference data to be used the ‘ground truth’ for the models that underlie AI systems. Present work then attempts to demonstrate the potential of synthesizing knowledge from the social sciences (psychometrics, survey science) related to sampling and measurement, with extant work on more useful content collection for use in machine learning tasks (metrology, perspectivist ground-truthing). Building on prior work reviewed herein, its main contribution is a synthesized framework that can be used to ground challenging phenomena in various media, following principles from prior work. A secondary contribution is a case study spanning several manuscripts, of a complex evaluation data set creation project. A third contribution, is knowledge directly applicable to the grounding of personal values in text, such as our annotation procedure, analysis of reference data, and statistics of interest for planning and estimating the costs associated. A final contribution is immediately applicable results that work towards estimating personal values in song lyrics using language models.

Included in this thesis are two manuscripts that further motivate the case study: 1) the first reviews strengths and weaknesses of datasets used in the field of Recommender Systems, 2) the second reviews how poor data practices in the field of Signal Processing related to datasets whose interconnections were poorly reported, misleading results. The case study demonstrates the use of principles from the Social Sciences to solve problems of representation and measurement across 4 manuscripts: personal values in song lyrics. In a 5th manuscript, the same principles are applied to a second form of text, political speeches, expected to vary in terms of use of ambiguous language. Despite the moderate success in automatically estimating values in lyrics, this work demonstrates a failure with speeches. It includes recommendations for analyses to observe the potential for success or failure, and to estimate cost via less expensive pilot studies. This thesis follows the case study with work that 6) highlights the potential for shortcomings in the interpretation of AI system evaluations should a more epistemologically sophisticated framework for evaluation not be adopted, and 7) highlights an important component of scientific infrastructure needed for rigorous work on data sets for Machine Learning: the treatment of scientific work as open-source artifacts.

# Background

## Reference data comes from humans

AI runs on data generated by humans. Reference data often uses responses from humans in the form of labels or annotations of content. “[D]ata annotation is the practice of labeling a set of digital representations of objects” (Cabitza et al., 2023). Although few studies have systematically examined the frequency of use of data from humans, it has been shown that reference data includes human input either explicitly or implicitly very often. Geiger et al. (2021) systematically review 200 randomly sampled papers from 3 broad domains, Social Sciences & Humanities, Life & Biomedical Sciences and Physical & Environmental Sciences. Out of the 140 studies that were classification tasks, 73.05% (or 103 papers) used labels derived from human responses as the reference. Geiger et al. (2020) reviewed 164 papers whose classifiers were trained on Twitter data and observed that 65% of the works reviewed used human annotations for the purposes of training. They further note that this quantity did not include human annotations used for validation, or other meta-data e.g. hashtags contributed by humans. In some domains the contribution of humans is in the form of digital traces, as in the domain of Recommender Systems where it was observed that, out of the most highly cited papers between 2018 and 2022, 86% of the datasets used were transaction data released by vendors such as Amazon or Yelp (Sav et al., 2023). Whether human input is explicit or implicit, it is present in almost all reference data.

Furthermore, training/reference data sets are often re-used, in some cases treated as *benchmarks* - measurement instruments used to produce comparable quantitative assessments of models (Welty et al., 2019) - magnifying their impact. Geiger et al. (2021) observed that 56.31% of the classification tasks that were reviewed (or 58 papers) used only ‘external’ human labels, i.e. labels that were not collected specifically for the work in the paper, Geiger et al. (2020) observed that 33.3% of the papers used external annotations, and Sav et al. (2023) observed that just 4 data sets appeared in at least 10% of works reviewed, with the most commonly used data set appearing in 33% of the works reviewed. Examining the most highly cited papers in IEEE CVPR from 2020-2022, the initial papers announcing the benchmark, along with the training and reference data received citation counts in the tens of thousands: Imagenet (Deng et al., 2009) shows over 52k citations, COCO (Lin et al., 2014) shows over 29k, Pascal VOC (Everingham et al., 2010) shows over 15k, according to SCOPUS as of April 2025. Thus, these human input data sets have the potential for long lasting effects on work that follows.

Although far more emphasis is placed on whether models achieve state of the art ‘performance’ or efficiency (Birhane et al., 2022), scholars over the past decade have attempted to draw attention to a lack of sophistication in how training and reference data are selected and evaluated (Aroyo & Welty, 2015). It has been argued that a focus on improving the data for a given task, will result in bigger gains than a focus on improving model[[5]](#footnote-26). Importantly, Hullman et al. (2022) show that optimizing for predictive accuracy does not absolve researchers from shortcomings in reference/training data, a situation exacerbated by the often re-use of data sets. A solution rather entails acknowledging that, whether deliberate or not, informed or not, organized or improvised, data are generated by process that may or may not be deliberately designed (Muller et al., 2021), yet would greatly benefit from design. Building on this, Welty et al. (2019) argue that datasets used to evaluate AI systems should be treated as measurement instruments in their own right. Drawing on the science of metrology, they propose that benchmark datasets ought to be evaluated using criteria analogous to those used for physical measurement tools.

## Common shortcomings of reference data design

Recent trends in Machine Learning (ML)— especially in deep learning — prioritize empirical performance over theoretical assumptions about the data generating process. A systematic analysis of highly cited ML works shows what is valued most: Performance, Generalization, Quantitative evidence, Efficiency, Building on past work, and Novelty Birhane et al. (2022). Unlike the social sciences (e.g. psychology), ML work ignores attempts to model the process that gives rise to the data, and aims instead at predictive models whose outputs fall within some accepted estimated error bounds, resulting in poor or even biased reference data design (Hullman et al., 2022).

Considering the ever-presence of human influence on the reference data, best practices, considerations, and frameworks from the social sciences could inform designs, but have yet to be broadly applied in the computational sciences (Beck et al., 2022; Jacobs & Wallach, 2021). One reason for this gap may be that ML researchers prefer to work on building systems and evaluating their performance rather than researching, designing and executing ground-truthing projects (Muller et al., 2021; Sambasivan et al., 2021). Another may be a lack of focus on these topics in textbooks, and thus in education more broadly (Geiger et al., 2020). A third may be that the social and computational sciences have conceptually different focci: the computational sciences focus on the statistical model the system with substantially less emphasis on the content, whereas the social sciences treat the statistical model as a means to better understanding the relationships in the content (Liem et al., 2018). Psychology research thus contains many more research projects in which datasets are collected using responses from people, whereas datasets tend to be re-used extensively in machine learning work (Geiger et al., 2021). A further more practical complication is that work on these topics lacks the acknowledgement that ground-truthing is indeed a measurement problem, and lacks a central academic ‘home’: where psychology and economics have psychometrics and econometrics respectively, fields dedicated to studying field-specific measurement practices, the study of ground-truthing lacks a central banner under which academic work can accumulate and disseminate.

Decisions such as the selection of items for training data (Hullman et al., 2022), and the collection of human responses for reference data (Beck et al., 2022), are part of a design of a process that results in data (Muller et al., 2021). Further, an investigation of 15 data science workers, Muller et al. (2021) observed common phases, which include determining the annotation scheme - a) all possible labels that can be attributed to digital representations of objects along with any relevant guidelines, b) the actual process of collecting labels, and c) the process by which the annotations are then aggregated into a single label. They note the difficulty of this work: issues in the annotation schemes are often discovered as annotation projects progress, requiring varying degrees of improvised adjustment. For any of these components, decisions are made that impact the resulting reference data, whether or not they are being made by design.

Commonly observed shortcomings of refernce data include: 1) representational biases in the content sampled for inclusion in training/evaluation datasets (Hullman et al., 2022), 2) a fallacious assumption of a single canonical ‘ground-truth’ when there are a range of reasonable interpretations (Aroyo & Welty, 2015; Cabitza et al., 2023), 3) measurement biases in the annotations collected (Beck et al., 2022; Hullman et al., 2022; Jacobs & Wallach, 2021), and 4) poor reporting of necessary information regarding the annotation-collection process (Geiger et al., 2021; Hullman et al., 2022).

An additional consideration that receives little attention is 5) the estimation of the number of annotations to gather, where fields that focus on gathering data from humans typically also have a strong emphasis on *a-priori* decisions, such as the pre-registration of calculated of target sample sizes estimated via statistical power analysis (Cohen, 1992), to mitigate sources of bias that come from the researcher. These considerations are absent in computational fields which appear to favor differing rules of thumb: e.g. in a well-cited textbook, Pustejovsky & Stubbs (2013) suggest to “have your corpus annotated by at least two people (more is preferable, but not always practical)”, whereas Artstein & Poesio (2008) suggest that “measuring reliability with only two coders is seldom enough, except for small-scale studies”.On the one hand, corpora tend to be very large, and resources are finite, making cost a primary factor in design decisions. On the other hand, rules of thumb lack clear substantiation in light of the both 1) the phenomenon being grounded and 2) the ambiguity of the media in which it is grounded. In other words, more variance is expected in annotation targets to the degree they are subjective or based on opinion (Beck et al., 2022), and more variance is expected in content to the degree to which it is ambiguous - i.e. can be interpreted in multiple ways - such as figurative language (Sandri et al., 2023). Further, some degree of variance will always be present when there are multiple annotations or ratings for a given piece of media independent of the target (Cabitza et al., 2023), based on the range of reasonable interpretations of that target in that media (Aroyo & Welty, 2015).

### Representational bias

When sampling content to include in training/test datasets, samples for the training/test sets will ideally be drawn from the same distribution as the content in which they will eventually be deployed. *Representation bias* in content selected for training and/or evaluation datasets refers to the degree to which relevant distributions in data used as reference and/or training data resemble distributions in the environment to which a system is deployed (Hullman et al., 2022). If data used for training under-represents parts of the input space of an algorithm that then estimates parameters from that input space, the model resulting will have higher error rates for those under-represented parts of the input space when deployed. If content is selected without appropriate design aimed at representing the population from which samples are drawn, the overall distribution will not represent the population it was drawn from. Thus, optimizing for predictive accuracy using very large datasets does not ‘absolve’ researchers from having to consider the data generating process, and this includes sampling pieces of content to be annotated.

Approaches to representation problems can come from Sampling Theory, which frames the problem as one of selecting elements of a population, from which a sample must be drawn, and where the aim is that measurements of interest in the sample resemble measurements of interest in the population (Groves et al., 2009). This framework is typically applied to selecting people for inclusion in survey studies, whereby their responses to questions lend themselves to inference about a target population. Although there is no ‘one-size-fits-all’ solution to sampling, this thesis makes use of *stratified random sampling* as a general strategy: namely, the identification of groups of elements within a population that may affect the measurements in question, and the random sampling of elements within the groups, with approximately equal observations. In principle, this allows for the representation of the groups in population, on the measurement of interest, with some margin of error (Groves et al., 2009).

### The perspectives of annotators

The field of machine learning tends to treat all annotation variance as noise rather than signal. Often multiple ratings per piece of content are collected, aggregated, and only then shared, forming a singular ‘ground truth’ for the aspect of the content being labelled or rated. The quality of annotations is typically assessed using inter-annotator agreement, where more agreement is typically thought to indicate higher quality data Aroyo & Welty (2015). Thus, it is assumed that there is a singular canonical truth for each aspect / content pair, comprised of aggregated human responses, visible as the general agreement of human response, and which forms a target to which we align our automated systems. To illustrate more accurate representation of human responses, however, Aroyo & Welty (2015) operationalize their term ‘crowd truth’ as the ‘gold standard’ being the probability that a sentence contains an element, based on the probability that an annotator annotated that sentence with that element i.e. the label isn’t represented as ‘present’ or ‘not present’, but as a probability that an annotator labelled it as such. The probability that they may label it as such may in part explained by certain characteristics of theirs, such as their backgrounds, personal experiences etc. (Beck et al., 2022).

Disagreement is common and never fully reducible (Cabitza et al., 2019). Cabitza et al. (2023) show that this is the case whether the task is typically thought of as subjective, e.g. NLP tasks (Aroyo & Welty, 2015), but also in tasks thought to be far less so, e.g. medical cases (Cabitza et al., 2019). Disagreement, observable as variance in the human input, is often removed via 1) adjusting annotator training and instruction so as to reduce variance in the human inputs at the time of collection, 2) adjusting annotations via discussion post-collection, thus allowing annotators to establish conventions, discuss views, and re-think their responses, or 3) completely post-hoc at the time of modeling, via methods like majority voting, without input from the annotators. Each method of reducing variance - e.g. thorough training for crowd-sourced workers, regular annotator meetings to resolve disagreements, or taking a mean of ratings or majority vote - may result in different data independent of content, or the phenomenon of interest being annotated in the content.

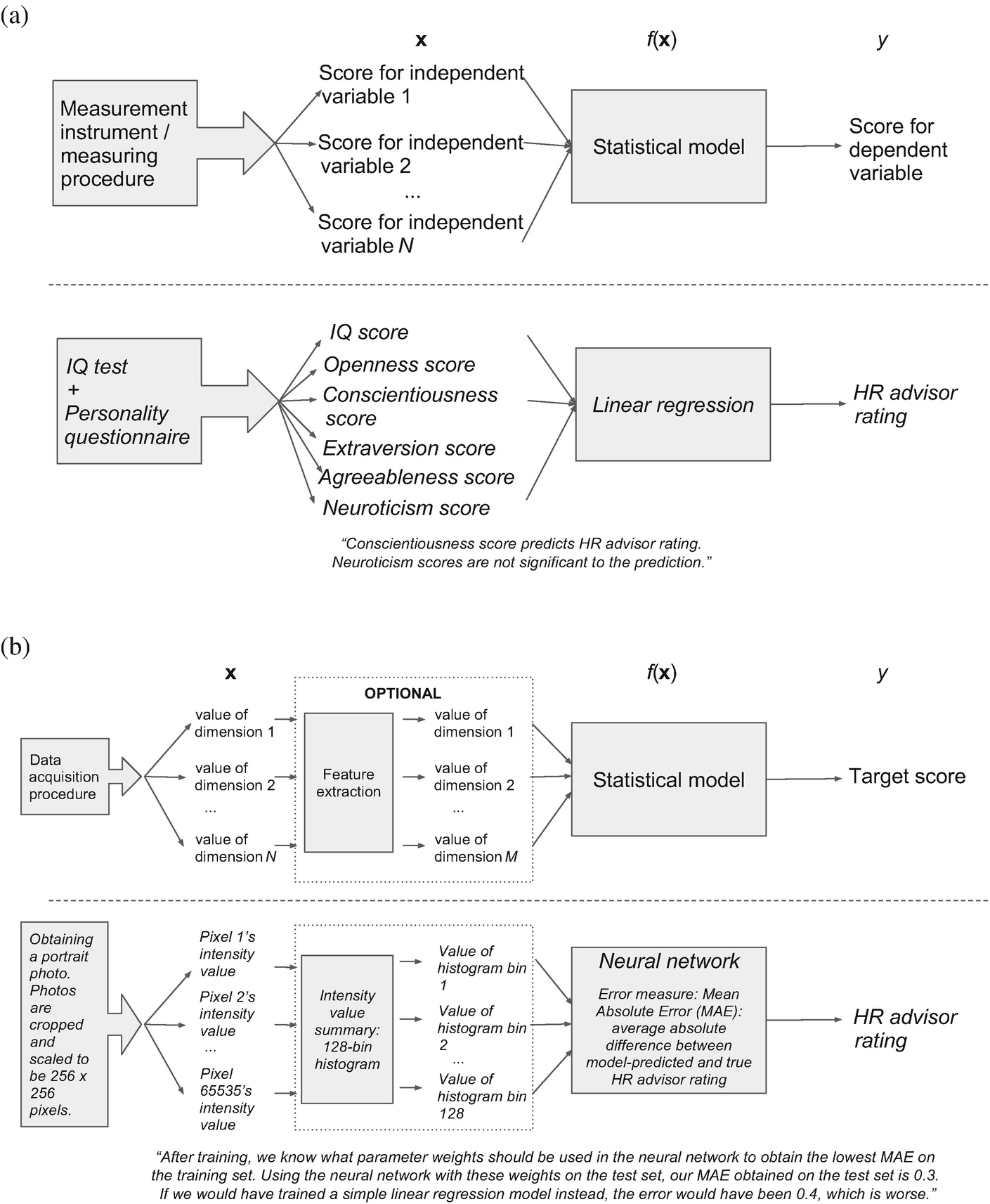
Further, variance in observed disagreement can be signal rather than noise. This signal may help to better understand the content being annotated: annotations may vary based on the ambiguity of the stimuli themselves, both in terms of the mode (audio vs. image vs. video vs. text), specific medium (Tweet vs. podcast transcript), or even the specific piece of content being annotated (Aroyo & Welty, 2015). Thus, not all pieces of content are equally unambiguous, and more ambiguous content is likely to result in greater variances in human input. This signal may help better understand the phenomenon of interest being annotated in the content: for at least some phenomena, the assumption that there is a single ground-truth to approximate with annotations doesn’t hold (Aroyo & Welty, 2015; Beck et al., 2022; Cabitza et al., 2023). More broadly, variances in the ratings may inform a finite “range of reasonable interpretations” of the phenomenon of interest being annotated in each piece of content, rather than a singular point. This signal may also help to better understand the background of annotators: people’s ethnic and/or cultural backgrounds may determine how they interpret content, and thus characteristics of the annotators may explain variance in the annotations. For example, although we expect hate speech exists, people’s perceptions of what constitutes hate speech may vary Beck et al. (2022). Showing that perceptions vary by identifiable characteristics, e.g. gender identity, ethnicity etc. may help unearth biases, whereby a single group perspective appears ‘objective’ (Cabitza et al., 2023).

Taking an approach to gathering reference data that attempts to account for the perspectives of the annotators is referred to as the *perspectivist*[[6]](#footnote-29) approach. It can apply to both the data annotation but also the modelling phase of ML projects, where benefits to ML models has been shown in a number of contexts (Cabitza et al., 2023). Although typically focused on the annotation of language data, perspectivist approaches can be broadly applied to annotations in reference data: *weak* perspectivist approaches involve taking perspectives into account while designing and collecting annotations e.g. by ensuring heterogenous raters and gathering enough ratings, as well as sharing and reporting the disaggregated data, but ultimately reducing annotations to a single label or rating for modeling. *Strong* perspectivist approaches involve taking perspectives into account for ground truthing and modelling phases.

Taking the perspectivist approach has a number of clear benefits, but also costs. It involves substantially more effort required to design the process that will result in annotations, higher costs in terms of the number of annotations and annotators needed in order to examine sources of variance, and challenges validating the data. In addition there are thus far few perspectivist modelling approaches that make full use of the variance in inputs (Cabitza et al., 2023). However, the perspectivist approach better reflects the reality that collecting annotations is a process that generates data with a number of relevant components (Hullman et al., 2022; Jacobs & Wallach, 2021). Further, it is a more complete report of the data resulting from the annotation process: the inclusion of the varying inputs in turn allows for better understanding of the content being annotated, the annotators annotating it, and the phenomenon of interest being annotated, which in turn allows for the development of models that make use of this information (Cabitza et al., 2023). This thesis makes use of stratified sampling among annotators in order to account for multiple perspectives.

### Measurement bias

The social sciences treat data from people as imperfect observations of a latent variable called a *construct* - like the effectiveness of a teacher, or recidivism i.e. the risk that someone will repeat a crime, or personality from the field of Psychology. Social and computational sciences traditionally have different focci: where the social sciences emphasize an interpretable meaning of and , where and are not always directly observable, the computational sciences instead focus on the statistical procedure that correlates in terms of (see Fig 1.). Applying the latent variable approach to the gathering of annotations, Jacobs & Wallach (2021) suggest there is a ‘measurement error model’ (a term they borrow from the field of Economics), that links the unobservable latent variable, and properties that we can observe - in our case, the data produced when people label or annotate. Thus, the annotations we observe can not be the ‘ground truth’ as such a thing is unknowable. Rather, each annotation is an imperfect indication that can be used to estimate the ground truth.

 Fig. 1: Liem et al. (2018)

To measure constructs the social sciences like Psychology, Survey Science and Cognitive Science research and develop *instruments*: standardized, systematic procedures designed to compare individuals (Cronbach, 1960). These are often in the form of surveys or standardized tasks designed to measure variables defined as latent, or indirectly observable. As one may measure one’s height with a ruler, one may acknowledge that no measurement is perfect, but estimate one’s latent ‘height’ via multiple measurements Jacobs & Wallach (2021). Similar to the ruler being an instrument to measure height, survey science treats the survey - the standardized process of collecting data from human input - like a measurement instrument. It thus seeks to minimize the influence of sources of ‘noise’: *Task Structure* involves refining specific wording and response options, including deciding on the inclusion of “I Don’t Know” or otherwise neutral response options, *Order Effects* involves strategies to randomly present content, as judgements of a specific piece of content are affected by perceptions of immediately previous pieces of content, and *Annotator Effects* which involves strategies to appropriately account for differences in perception based on the backgrounds, experiences and opinions of the annotators (Beck et al., 2022).

A number of fields provide frameworks for assessing the quality of a measurement instrument, including psychometrics (Jacobs & Wallach, 2021), survey science (Beck et al., 2022), and metrology - the science of measurement - (Welty et al., 2019). For instance, the concept of *reliability* asks whether similar inputs consistently produce similar outputs, either across annotators (inter-rater reliability) or over time (test-retest reliability). The related concept of *precision* in metrology, separates the similarity of measurements from an instrument into *repeatability*, the similarity of measurements given that the operator, equipment, calibration, environment, and time between measurements are held constant, and *reproducibility*, the similarity of measurements given that the aforementioned are not held constant (Welty et al., 2019).

Beyond consistency, *validity* addresses whether the instrument is actually measuring what it claims to measure (Jacobs & Wallach, 2021). This includes checks for face validity (does it seem plausible?), content validity (does it cover the full scope of the concept?), and structural or substantive validity (do the internal patterns make sense given extant theory?). Other forms such as convergent and discriminant validity test whether the measure behaves as expected relative to related or unrelated constructs, while predictive, hypothesis, and consequential validity consider what the measurement enables: does it support useful predictions, align with theoretical expectations, or have appropriate consequences in applied contexts? Although there is no one-size-fits-all solution to estimating the quality of an instrument, these various tools provide insights into whether the measurements appear to have qualities fitting of good measurements.

### Inadequate reporting

Despite the central role that human-labeled data play in machine learning, studies often provide insufficient documentation about how these data were created. In their systematic review, Geiger et al. (2021) and Geiger et al. (2020) found that many ML papers fail to adequately describe the processes used to create ‘ground truth’ labels, leaving unclear what exactly is being measured or how. As a result, the reference data often function as opaque black boxes, preventing meaningful scrutiny of what a model has learned. This is particularly concerning as they show that such datasets are reused across multiple studies, amplifying the impact of unreported or poorly understood annotation processes. Building on this, Hullman et al. (2022) argues that when reference data are under-specified, it becomes impossible to determine what data-generating process a trained model actually represents. Without transparency about how labels were created, we cannot evaluate the model’s fitness for deployment, its fairness, or its generalizability.

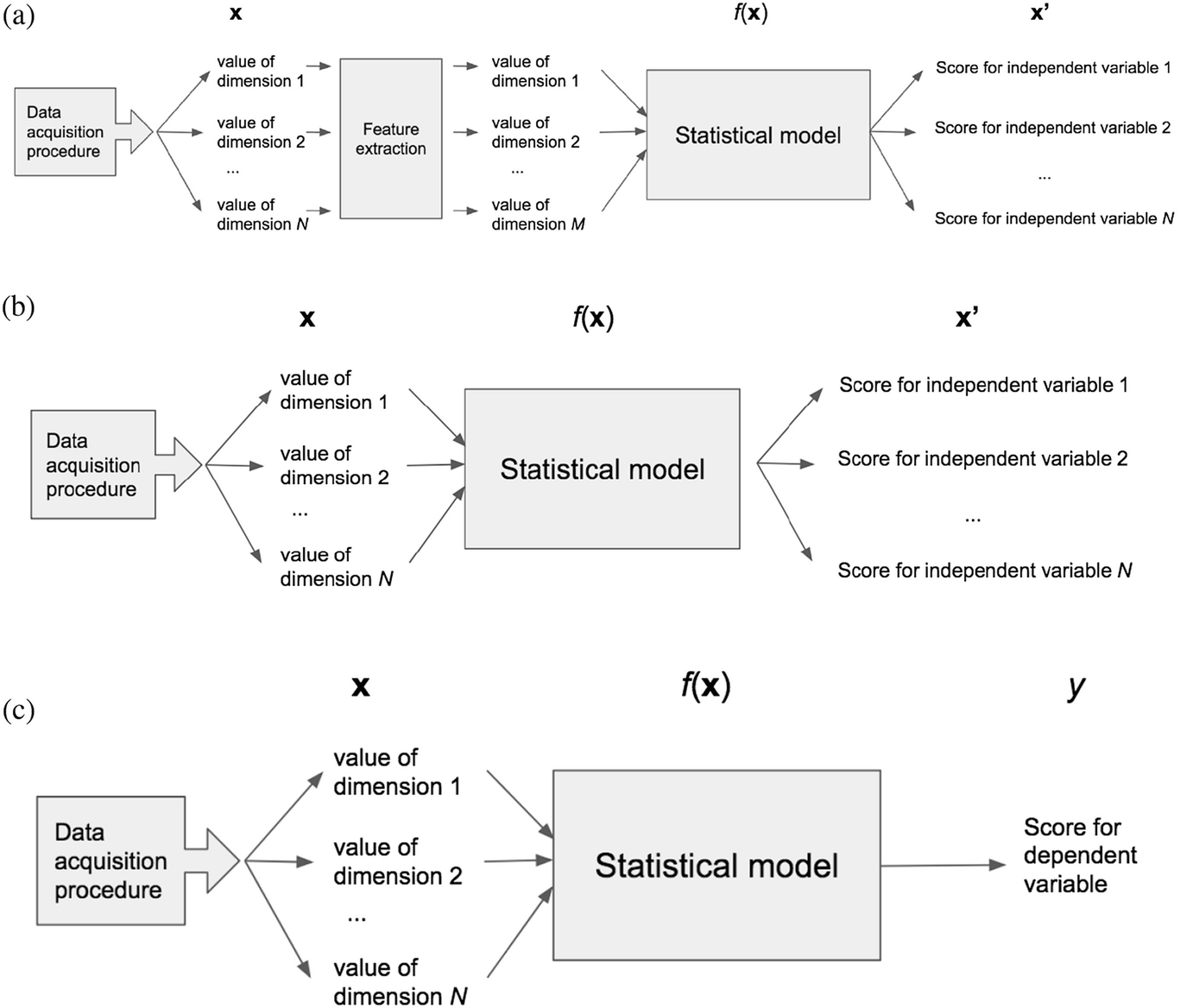
Geiger et al. (2021) provide concrete recommendations for improving transparency and accountability when reporting annotation procedures. They argue that researchers should report who the annotators are (including demographics or expertise where relevant), how they were recruited, and what task instructions were given. Additionally, they recommend documenting the labeling environment, such as tools or interfaces used, and whether annotators worked independently or collaboratively. Reporting should also include measures of inter-annotator agreement, details on how disagreement was handled (e.g., aggregation method, arbitration), and any quality control mechanisms applied. These reporting practices not only support reproducibility and critical evaluation but also help surface the social and epistemic assumptions embedded in the annotation process — assumptions which directly shape the model’s understanding of the world. Cabitza et al. (2023) further emphasize that adequate reporting should include details such as the number and expertise of raters, their incentives, instructions provided, time spent per annotation, inter-rater agreement metrics, the method used to aggregate annotations, and any confidence measures. These elements are necessary not only for reproducibility but also for evaluating the quality and appropriateness of the annotation process itself. Without them, assessments of model performance risk being built on shaky foundations, misrepresenting both the model and the phenomenon it is intended to capture.

# Present Work

This thesis attempts to synthesize recommendations on how to better collect data to be used as reference and possibly training. It accounts for the aforementioned shortcomings in the design of study, using recommendations from the social sciences and syntheses of material from survey science, metrology.

This thesis attempts to further the field in the following ways:

* we attempt representative sampling of both media and respondents
* we aim to estimate 10-dimensional psychological construct
* we select media that is ambiguous (i.e. that will result in subjectivity in the ratings) as well as media that we expect not to be ambiguous for comparison
* we estimate a-priori the number of ratings necessary rather than assuming
* we take into account perspectives

The primary case study of this thesis works towards path (b) in Liem et al. (2018), shown in: , and showcases a design for a challenging ground-truthing project, in terms of the complexity of the phenomenon of interest, ambiguity in the media that selected and annotated. It incorporates design choices to address the aforementioned shortcomings into a singular framework, guided by best practices in the social sciences, which it then extends.

Specifically:

* We attempt to mitigate representation biases in the content we select for annotation by using a stratified sampling strategy.
* We attempt to mitigate measurement biases by treating the target measurement as a latent variable, and the survey we used to gather annotations as an instrument. We build on work that validated a questionnaire for measuring constructs, and estimating its reliability and structural validity when used for annotations.
* We account for the potential of multiple perspectives in our dataset by recruiting participants from relevant subgroups in a single target population.
* We report the details of the annotation collection process, and share the disaggregated dataset of the annotations
* We further show how to estimate the number of annotators

We demonstrate the potential of this framework by grounding a complex phenomenon (a 10-dimensional construct, Personal Values) in ambiguous text (song lyrics). We further show an

When sampling content to include in training/test datasets, samples for the training/test sets will ideally be drawn from the same distribution as the content in which they will eventually be deployed. *Representation bias* in content selected for training and/or evaluation datasets refers to the degree to which relevant distributions in data used to train and/or evaluate systems resembles the distribution in the environment to which it will be deployed (Hullman et al., 2022).

Measurement bias in the annotations collected from humans may also bias

Perspectivism Cabitza et al. (2023) recommendations: - complete labeling schemes, including ‘i don’t know’, ‘none of these’ etc. categories, and the ability to express issues with label set

Reporting

We add: a priori rating number estimation

And although imperfect as leaderboard scores can be gamed, and do not perfectly represent the deployment environment, the typical leaderboard approach has shown evidence that progress can be made towards a target. This thesis thus represents an attempt to define the target better.

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