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, 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.

## Common shortcomings of reference data design

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). Commonly observed shortcomings of this process include: 1) measurement biases in the annotations collected (Beck et al., 2022; Hullman et al., 2022; Jacobs & Wallach, 2021), 2) a fallacious assumption of a single canonical ‘ground-truth’ (Aroyo & Welty, 2015; Cabitza et al., 2023), 3) representational biases in the content sampled for inclusion in training/evaluation datasets (Hullman et al., 2022), 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?**), based on the range of reasonable interpretations of that target in that media (**arroyo?**).

### 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 to evaluate and possibly train systems resembles the distribution in the environment to which it will be 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. In other words, optimizing for predictive accuracy using very large datasets does not ‘absolve’ researchers from having to consider the data generating process.

### Measurement bias

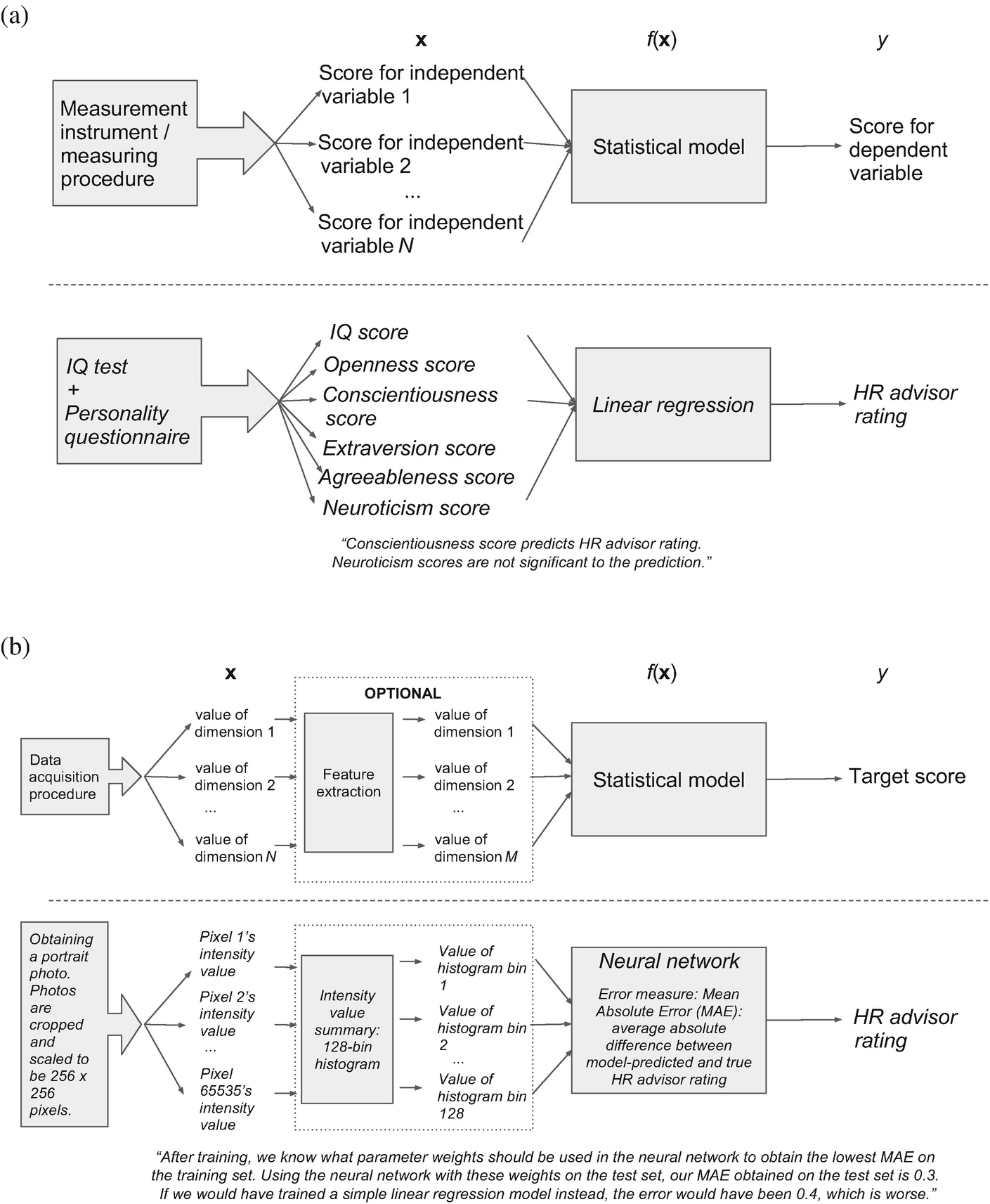
Recent trends — especially in deep learning — prioritize empirical performance over theoretical assumptions about the data generating process. A systematic analysis of highly cited ML works shows that Performance, Generalization, Quantitative evidence, Efficiency, Building on past work, and Novelty are the primary values in ML work 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, assuming it cannot be learned, and aims instead at predictors that fall within accepted estimated error bounds (Hullman et al., 2022). This is problematic as this kind of optimization doesn’t resemble real world deployment.

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, which then may see years of re-use. The quality of annotations is 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, which forms a target to which we align our automated systems.

However, disagreement is common. 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 extend to tasks thought to be far less so, e.g. medical cases (Cabitza et al., 2019). In both scenarios, 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 re-think their responses, or 3) completely post-hoc at the time of modeling, via methods like majority voting, without input from the annotators. Clearly, the data generated from a process that may result from e.g. thorough training for crowd-sourced workers, may vary from one in which annotators meet regularly to resolve disagreements.

#### Modelling the data-generating process

Social and computational sciences traditionally have different focci. Where the social sciences emphasize an interpretable meaning of x and y, and where design design is informed by theory, the computational sciences focus on the learning procedure itself.

 Fig. 1: Liem et al. (2018)

annotations aim to measure a latent variable. Jacobs & Wallach (2021) there is a ‘measurement error model’ (taken from econ) that links the unobservable latent variable, and observable properties. in annotations this is via individual observations. although paper focuses on attempts at measuring constructs (risk of recidivism, teacher effectiveness, patient benefit) they also show that even ‘representational measurements’ like height, are essentially a latent variable

Aroyo & Welty (2015) operationalize ‘crowd truth’ with an illustration where the ‘gold standard’ is 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 probablility
* thus the ‘crowd truth’ attempts to capture the ‘range of reasonable interpretations’

Beck et al. (2022): we should expect more variance to the degree that tasks measure opinion show work on an intuitively perspective-based use-case: hate speech

Aroyo & Welty (2015) for myth 6: disagreement indicates that the media being rated is ambiguous.

#### Human judgments are imperfect

Griffin & Brenner (2004) review errors and biases in human judgements[[6]](#footnote-33)

Griffin & Brenner (2004) review errors and biases in human judgements[[7]](#footnote-34)

* over/under prediction: confidence score is higher/lower than accuracy
* over/under extremity: confidence is more extreme at ends

also reviews possible reasons:

* optimistic overconfidence
* confirmation bias
* case-based judgment
* ecological probability
* error model (psychometric model)

#### Treat annotation generating process as an instrument

Beck et al. (2022)

* annotation collection requires design thinking
  + Task Structure: specific wording and response options, including debates over the inclusion of “I don’t Know” option
  + Order Effects: specific judgements are affected by previous perceptions
  + Annotator Effects: backgrounds, opinions, experiences of respondents affect responses

Jacobs & Wallach (2021)

* reliability: do similar inputs to a measurement model present similar outputs?

test-retest: are measurements of an unobservable latent construct taken at different times via a measurement model similar, assuming the construct hasn’t changed?

* validity: is it ‘right’?

no single test for validity on purpose, because it requires thinking. do our measurements:

* face validity: look plausible/ sensible?
* content validity: capture the construct?
  + structural validity: show the inter-correlations we expect?
  + substantive validity: capture only observable properties thought to be related to the construct?
* convergent validity: show correlations with other validated methods?
* discriminant validity: show correlations with other construct/properties thought not to be related to the construct?
* predictive validity: show correlations with constructs/properties thought to be related, but not in the operationalization?
* hypothesis validity: shed light on relevant hypotheses about the construct being measured?
* consequential validity: allow for the consequences obtained from the measurement model to be assessed?

##### ML ignores perspectives of annotators

Cabitza et al. (2023): whether the target of the annotation is a subjective phenomenon or not, disagreement is always irreducible. Yet ML typically assumes there is a single ‘ground truth’, and its best indicator is inter-annotator agreement. But taking the perspectives of the annotators into account, both in the data annotation but also the modelling phase of ML projects has recently been shown to benefit ML modelling in a number of contexts.

weak perspectivist approach: taking perspectives into account while designing and collecting annotations, but ultimately reducing annotations to a single label or rating.

strong perspectivist approach: taking perspectives into account for ground truthing and modelling phases.

benefits of this approach:

* is congruent with the reality of collecting annotations
* includes the signal in the variance of labels or ratings
* avoids majority group perspective appearing to be ‘objective’
* allows for the modelling of human errors and variances
* allows for uncertain, fuzzy, or soft model development
* more complete report of the data generating process, as it also reports uncertainty

downsides:

* multiple raters, and therefore costs/time/rater availability are issues
* need for perspectivist ML approaches
* validation becomes more challenging

recommendations:

* complete labeling schemes, including ‘i don’t know’, ‘none of these’ etc. categories, and the ability to express issues with label set
* enough raters
* heterogenous raters
* adequate reporting:
  + number of raters,
  + rater expertise
  + incentive
  + instructions
  + length of time for labelling
  + inter rater agreement
  + aggregation method
  + confidence

Beyond errors in judgment are questions about the target for the annotations. For at least some phenomena, the assumption that there is a single ground-truth to approximate with annotations doesn’t hold Aroyo & Welty (2015).

Aroyo & Welty (2015)

7 ‘myths’ of human annotation:

* there is one truth
* disagreement is bad
* detailed guidelines help
* experts are better
* one annotator is enough
* all items are created equal
* once done, forever valid

For myths 1 and 2:

* list examples from NLP where the disagreement from annotators is sensible
* they argue that the assumptions of a single ground truth, and that disagreement is indicative of poor annotations are both false.

##### Inadequate reporting

Geiger et al. (2021) ML science studies inadequately report ‘ground truth’

Hullman et al. (2022) thus we cannot know what data generating process the resulting model represents

[perhaps cat image parable here?]

An investigation of 15 data science workers, Muller et al. (2021) observed common phases, which include determining the annotation scheme - all possible labels that can be attributed to digital representations of objects along with any relevant guidelines, the actual process of collecting labels, and 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.

# Tools from Social Science can help

### Issues with sampling

Solutions to sampling problems can come from sampling theory: Groves et al. (2009)

considerations:

* sampling frame: the elements in from populations that you have access to
* ineligible units: elements in the sampling frame that are not your target
* undercoverage: elements from target population that are not in the frame

solutions:

* stratified sampling

### Issues with instruments

Beck et al. (2022)

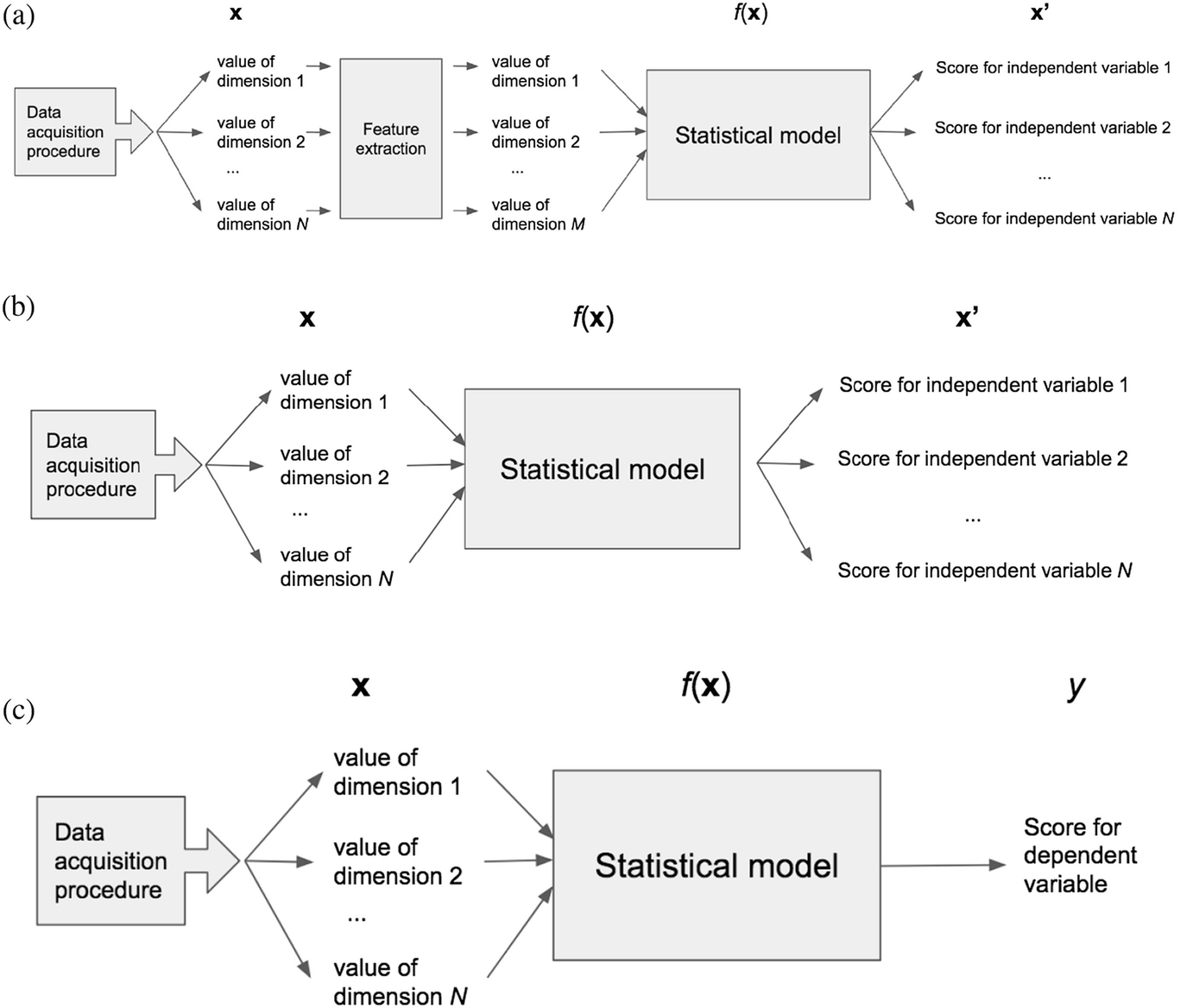
* annotation collection requires design thinking
  + Task Structure: specific wording and response options, including debates over the inclusion of “I don’t Know” option
  + Order Effects: specific judgements are affected by previous perceptions
  + Annotator Effects: backgrounds, opinions, experiences of respondents affect responses

[another ref that describes the target as a latent variable]

# Present Work

We incorporate these considerations in the design of our study, and attempt 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

case study of this thesis works towards path (b) in Liem et al. (2018) shown in: 

This thesis incorporates techniques and considerations from the social sciences to address the aforementioned shortcomings.

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. It focuses unambiguously on the aspect most relevant to the

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

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Measurement bias in the annotations collected from humans may also bias

Perspectivism

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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2. https://en.wikipedia.org/wiki/Artificial\_intelligence [↑](#footnote-ref-21)
3. https://en.wikipedia.org/wiki/Statistical\_parameter [↑](#footnote-ref-22)
4. https://en.wikipedia.org/wiki/Algorithm [↑](#footnote-ref-23)
5. https://www.youtube.com/watch?v=06-AZXmwHjo [↑](#footnote-ref-26)
6. Griffin & Brenner (2004) note that much of this work was about people guessing knowledge from an almanac, and then guessing how accurate they were [↑](#footnote-ref-33)
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