THE PSYCHOLOGY BEHIND AI - INVESTIGATING BIASES IN CROWDSOURCED ATOMIC DATA THROUGH A SUSTAINABILITY LENS

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Abstract:

Progress towards accomplishing the Goals of the UN 2030 Agenda for Sustainable Development has been limited, and learning for environmental sustainability is fraught with challenges. Biases developed as an evolutionary mechanism for human survival; however, they can also hinder environmental sustainability in situations with unclear, uncertain outcomes. Crowdsourced databases, which are used to train Artificial Intelligence models via machine learning, often contain biases; therefore, this study presents a secondary data analysis of extracted data from the ATOMIC commonsense knowledge base. The extracted data consists of 1145 if-then statements linked to the environment. Binomial logistic regression was used to test whether a statement being biased or not predicts whether a statement is environmentally sustainable or unsustainable. The relationship between probability neglect and present bias and unsustainable statements was found to be statistically significant ($p < 0.001$), supporting the hypothesis that being biased corresponds to acting in an unsustainable way. These results are discussed through the lens of learning theory and the evolutionary psychology framework. Although limitations are present, this line of research has numerous global implications and has the potential to inform research both on Natural Language Processing (NLP) and educational programs targeting environmental cognitive biases. This has the potential to contribute to better educating humanity about the consequences of their actions and how to approach the environment in a more healthy, holistic and sustainable way.

Keywords:

Crowdsourcing, Sustainability, Bias, Machine Learning, Evolution.

INTRODUCTION

The United Nations (UN) adopted the 2030 Agenda for Sustainable Development in 2015. [1] This agenda, aside from its economic and social ramifications, also tackles environmental protection. [2] Some progress has been made in this domain, including aspects such as water, biodiversity and soil. [3] Nonetheless, learning for environmental sustainability is marked by distinct setbacks and hurdles. [4] The cause-and-effect events linked to the environment are inherently probabilistic, delayed and are not limited to one domain. [5] [6] Its complexity is further accentuated by psychological distance (a construct with dimensions involving social, spatial, hypothetical and temporal distance), which characterizes how humans perceive, learn from and act upon climate change. [7]

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According to learning theory, learning in such complex settings as the environment is not feasible without inductive biases (such assumptions serve to build a hypothesis based on a finite set of data). [8]

Generally, biases are also one of the core model limitations of commonsense knowledge bases. [9] Sources of commonsense knowledge are frequently used to train Artificial Intelligence (AI), concretely via machine learning and/or deep learning. [10] [11] One recent example of such a knowledge base is ATOMIC, an atlas of machine commonsense. Information in ATOMIC is displayed in the form of approximately 877k if-then relations/statements reflecting inferential knowledge. [12] ATOMIC was compiled via crowdsourcing – a concept which appeared relatively recently. [13] Crowdsourcing denotes the activity of delegating the completion of a task to a sizable, heterogeneous sample of individuals. [14] With respect to such a methodology, it is acknowledged in the literature that crowdsourced databases similar to ATOMIC might be filled with biases. [15] [16] [17]

In light of all that has been stated above, the aim of this paper is to conduct a secondary data analysis of biased statements within ATOMIC. This will be done through the lens of environmental protection and sustainability. Broadly speaking, a cognitive bias is defined as "cases in which human cognition reliably produces representations that are systematically distorted compared to some aspect of objective reality". [18] The phenomenon has been discussed as tightly related to evolutionary psychology, especially in the context of making judgements under uncertainty (which is relevant to environmental decision-making). [19] Natural selection is the sole evolutionary process that, over time, provides biological species with the traits referred to as "adaptive", and which are essential for survival in an ever-changing environment. [20] According to evolutionary theory, cognitive biases could manifest for three primary reasons:

1. Natural selection could find an easier and quicker path/solution that is successful in the majority of situations.
2. They can manifest as a result of the biased approaches in response to adaptive issues, yielding lower error costs compared to non-biased approaches, which is often referred to as error management bias.
3. When an individual is trying to do something their abilities are fundamentally not geared towards, an apparent bias can manifest itself – this is also known as an artifact. [21]

It is important to note that both the concept of error and artifacts are analogously present in machine learning as well. For example, the probability of error is central in the Probably Approximate Correct model proposed by Leslie Valiant in 1984. [22] Likewise, artifacts and false signals can appear in conjunction with noisy and messy data in machine learning. [23]

In biological species, several processes of learning have been described, including variants of imitation, Pavlovian conditioning, instrumental conditioning, etc. [24] Evolution in itself has been linked to learning dynamics inside a comprehensive mathematical framework of learning theory, through explanatory mechanisms like neural networks. [25] The two concepts have formally been labelled as equivalent in other contexts as well, amongst which are the application of Bayesian learning within sexual preferences and the evolution of genetic systems; this notion also casts a light on complex research topics such as the "evolution of evolvability". [26] Rupert Riedl – one of the founders of evolutionary developmental biology – put forth the idea that evolution works precisely via this mechanism, which explains how it has enhanced its own capacity to evolve as a process. [27] One study quantitatively simulated evolution on rugged fitness landscapes (a setting in which genes and environment interact via adapting, with peaks and lows). It determined, based on gene-phenotype maps, that developmental structures which resemble the pattern of how phenotypes are constrained would be favoured by short-term natural selection and, in turn, impact further changes. [28] This can partly explain how biases are perpetuated across generations, and is analogous to constraints in the hypothesis space in the PAC learning algorithm. In a similar vein, one paper, on the basis of a recurrent non-linear gene regulation network experiment, argues that evolution's illumination of regular patterns (generalization) is related to both human and machine learning. [29]

Taking into account all of the above, the types of cognitive biases that will be investigated in this paper are present bias and neglect of probability. These biases were selected because the consequences of environmental actions are typically both delayed and probabilistic. [5] [6] [30]

Present bias is generally studied within the framework of behavioral economics. [31] It refers to the tendency to prefer a modest reward immediately, rather than visualize the bigger picture long-term and pursue bigger rewards. [32] In terms of terminology and definition, it is closely linked to (but distinct from) temporal discounting. [33] The term itself was coined in the 1950s, but writings about it stretch back to Ancient Greece, with the poet Hesiod dealing first with the topic of seeking immediate pleasures. [34] Present bias can result in procrastination as well and has multiple adverse dimensions to it, including lower adherence to health guidelines. [35] [36] When it comes to environmental sustainability, one empirical study specifically found that individuals who are more present-biased tend to invest less in household appliances which are energy-efficient. [37] Similarly, business people who exhibit present bias are more inclined towards carbon credit sales and abatement as opposed to sustainable alternatives aimed at lowering harmful emissions. [38] On the other hand, it has also been shown that future-oriented individuals tend to engage more in pro-environmental behavior. [39]

Neglect of probability refers to the cognitive bias wherein people, upon making choices, do not account for the likelihood of an event when placed in an uncertain situation that evokes strong emotions. [40] Findings suggest that this bias impacts lives in various ways. For example, one study found it to be connected with the phenomenon of social distancing during the COVID-19 pandemic in Japan. [41] Neglect of probability is especially present in the evaluations of performance. [42] The famous Monty Hall Problem illustrates this bias well. [43] In terms of sustainability, this materializes in the form of wrongly assessing probabilities of climate change, because this is usually not intuitive to humans, as is quantifying environmental outcome intensities. [44]

The research question addressed herein is: Are mental representations encoded in ATOMIC's if-then statements (in the context of sustainability) statistically linked to biases (neglect of probability and present bias)? More concretely, this paper will test whether a statement being biased predicts whether a statement is environmentally sustainable. Based on past literature, the hypothesis is that a meaningful statistical relationship will be established, and that being biased will correspond to unsustainable thinking. The novelty of the question lies in the fact that never before has environmental causality in conjunction with biases as psychological constructs been studied with crowdsourcing as the backdrop, and therefore, this paper fills a gap in previous research.

2. METHOD

The methodology of this paper consists of a secondary data analysis conducted via chi-square test of independence (used for finding associations between nominal variables) and binomial logistic regression in SPSS statistical software package. The statistics were chosen in accordance with both recommendations and best practices from prior research on psychology and other areas. [45] [46] [47] The two variables investigated are: biased statements (categorical binary independent variable) and causal environmental if-then representations (dependent variable, and treated as dichotomous herein). Given that the dependent variable is also classified as binary (essentially in line with Boolean logic), this means that it follows the Bernoulli distribution. [48]

Criteria for categorizing specific statements (consisting of events, intentions, reactions, attributes and effects) as either probability neglect or present bias or non-biased were based on classification of similar examples of human statements from the existing literature. [49] [50] For instance, the ATOMIC event "PersonX throws it on the ground" followed by "to express his disapproval" would be treated as present bias. This represents an asymmetry in mental representation. Criteria for classifying statements as environmentally sustainable were based on the very principle of what sustainable means – being capable of maintaining an ecological homeostasis of Earth's natural environment and supporting the rational use of resources so as not to harm the needs of future generations. [51] Statements which showed signs of such tendencies (or lack thereof) were systematically selected.

Data were obtained from the publicly available dataset by extracting its subset from the 2019 ATOMIC research paper. [12] Filtering of the selected data was done manually. Search keywords relevant to the environment (e.g., "sustainability", "pollution", "nature", etc.) were deployed in the appropriate file in order to generate the final dataset for the purposes of this paper. A total of 1145 causal statements were analyzed within the knowledge base subset. The contingency table for the filtered data is shown in Table 1. The total percentages of the data are: 33.4 % for biased statements and 66.6 % for non-biased statements, as well as 65.1 % for environmentally sustainable statements and 34.9 % for environmentally unsustainable statements.

Table 1. Contingency Table of the Data

Presence of bias	Type of environmental statement		Total
	Environmentally sustainable	**Environmentally unsustainable**	
Biased statements	138	244	382
Non-biased statements	607	156	763
Total	**745**	**400**	**1145**

Table 2. Binomial Logistic Regression Results with Environmentally Sustainable or Unsustainable Statements as the Dependent Variable

		95 % confidence interval	
p	**Odds ratio**	**Lower**	**Upper**
< 0.001	6.880	5.236	9.039

3. RESULTS

Within the sample of ATOMIC environmental if-then representations, the distribution of biases (present bias and probability neglect) was significantly different ($p < 0.001$), with those making environmentally sustainable statements having 12.1 % of biases and the environmentally unsustainable ones having 53.0 % of biases, cumulatively. This was found via the chi-square test of independence. The phi-coefficient and Cramer's V were equal to 0.429 (demonstrating a moderately strong statistical link). As for the previously discussed percentages, these can be computed based on the data provided in Table 1. Overall, these results are indicative that probability neglect and present bias may be associated with being environmentally unsustainable upon expressing thoughts on related matters.

Table 2 displays the results of binomial logistic regression for the relationship between cognitive biases and environmental sustainability within statements. Probability neglect and present bias significantly ($p < 0.001$) elevate the odds ratio for environmentally unsustainable if-then representations to 6.880. Such an odds ratio is generally considered very large in research. [52]

4. DISCUSSION

Previous studies have found that cognitive biases are related to the presence/absence of individual environmentally sustainable actions, views and reasoning. [44] The present paper supports this finding, which is in line with the hypothesis formulated at the beginning. Based on the data presented in Table 2, it can be inferred that the type of ecological statement (biased vs. non-biased) predicts (with a high odds ratio) whether the if-then representations in commonsense knowledge are sustainable or not. Present bias and probability neglect increase the prevalence of unsustainable statements.

Limitations of these results encompass the fact that the ATOMIC database does not list demographics (such as age, gender, country, etc.) of the participants (which could be a potential confounding variable). In extension, the biases themselves could be partly a product of the methodology the researchers used to populate the knowledge base, which involved annotation by anonymous human participants. Problems with the validity of crowdsourced data generally span from (but are not limited to) "self-selection bias, participants' non-naivete, to inattentiveness and self-misrepresentation." [53] The data analysis deployed in this paper did not account for the fact that certain actions, whilst being environmentally sustainable, are not executed primarily for that reason but rather a more self-serving one and vice versa. Also, the high odds ratio of 6.880 in the binomial logistic regression and the statistically significant association found may not hold for a specific sample with a specific size and structure, and in the presence of covariates. An odds ratio itself does not correspond necessarily to relative likelihoods. [54] The fact that probability neglect and present bias were not separately studied, compared and contrasted (given the lack of sufficient extracted data to do this statistically) gives an incomplete picture of the results.

The root cause of the above findings can be traced back to evolutionary psychology and learning theory. More specifically, one neuro-evolutionary framework outlines how biases come from ingrained elements of the evolving human brain. [55] Such a theoretical framework gives deeper causes for personal decision-making and executive functions within the domain of environmental sustainability. [56] The core components of the evolutionary theoretical framework have also been explained through the lens of learning theory. [25] [27] [30]

The crowdsourced ATOMIC database is an output of learning. It represents an example of commonsense knowledge used to train AI models and, given that its statements originate from humans, it is critical to objectively assess its potential biases and any forms of noisy data. [57] The idea is to prevent artificial agents (machines) from perpetuating such biases. [58] Present bias and probability neglect as psychological constructs are especially relevant for environmental mental representations, because of just how probabilistic and delayed the intricacies of any ecological event/setting are. [5] [6] This notion aligns the above results with the evolutionary framework and learning theory – it shows how humans adapt and simplify their reasoning when faced with abstract and uncertain outcomes. This can be interpreted as an inherited inclination stemming from human ancestral settings – humanity has favoured immediate outcomes and relied on disregarding probabilities as an evolutionary mechanism of survival and Life History Strategy for thousands of years. [59] In learning theory terms, a human learner (as a biological agent) is placed in a partially observable setting (the environment) and, in order to learn the behaviour of the target function based on available labeled examples, he/she generalizes (a critical feature of learning), and in doing so, sometimes makes wrong assumptions. This is often because of incomplete/missing information, hindering learnability. [60] However, if the purpose (e.g., survival) is served well and the behaviour is rewarded in the specific settings, this enters the ongoing evolution of humanity, and evolves into either an adaptive or maladaptive trait across generations. ATOMIC depicts what environmental cause-and-effect (which has evolved from human ancestral contexts) manifests like once it has gone through a crowdsourced knowledge base, and is therefore relevant for machine learning.

Crowdsourcing has social, cultural and technological implications with global ramifications. [53] ATOMIC itself was designed to aid Natural Language Processing development, something which this paper strives to contribute to. [12] It is important to see how humans cognitively interpret environmental action via crowdsourcing in machine learning. Identifying the correct cognitive biases in a timely manner can inform educational approaches directed towards reducing them. [61]

If it could be better understood how people perceive actions which either help or harm nature, then this implies schools could also develop better strategies to tackle environmental challenges by integrating this knowledge into educational practices and civic engagement. [62]

5. CONCLUSION

Results of the present study support the contention that probability neglect and present bias increase the likelihood of generating environmentally unsustainable mental representations. Further research is needed to determine which evolved traits of humans make them more susceptible to these biases. A recommendation for future research is to conduct psychological research (e.g., personality) into those who participate in crowdsourcing, as well as account for demographics, and conduct cross-cultural comparisons to see whether the aforementioned biases evolved in a universal manner across intercultural settings. This has implications for society as a whole and has potential to contribute to better educating people about the consequences of their actions and how to approach the environment in a more healthy, holistic and sustainable way.

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