Measuring a Text’s Fairness Dimensions Using Machine Learning Based on Social Psychological Factors

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Fairness is a principal social value that can be observed in civilisations around the world. A manifestation of this is in social agreements, often described in texts, such as contracts. Yet, despite the prevalence of such, a fairness metric for texts describing a social act remains wanting. To address this, we take a step back to consider the problem based on first principals. Instead of using rules or templates, we utilise social psychology literature to determine the principal factors that humans use when making a fairness assessment. We then attempt to digitise these using word embeddings into a multi-dimensioned sentence level fairness perceptions vector to serve as an approximation for these fairness perceptions. The method leverages a pro-social bias within word embeddings, for which we obtain an F1= 81.0. A second approach, using PCA and ML based on the said fairness approximation vector produces an F1 score of 86.2. We detail improvements that can be made in the methodology to incorporate the projection of sentence embedding on to a subspace representation of fairness.

Keywords: Text analysis, NLP, Fairness, Social Cognition, Psychometrics

Introduction

A lay person reading a document, which describes a person acting with malice towards another is able to predict that a conflict is likely due to the presence of an unfair act. This judgment has its roots in both social and biological factors owing to humans being a highly evolved social species (Tomasello 2014). We ask, is it possible to approximate these perceptions, and incorporate them into a form of measurement tool? One that would allow a sentence describing the interactions of two or more individuals to be approximated as being fair or unfair?

While natural language processing (NLP) for textual analysis has been used across a large number of disparate domains such as personality detection (Youyou, Kosinski, and Stillwell 2015), healthcare (Gaudet-Blavignac et al. 2021; Le Glaz et al. 2021, 202; 2021), product reviews (Paruchuri et al. 2021) and dialect detection (Al Shamsi and Abdallah 2021), a search of the literature for a measure that is able to detect how fair a sentence is yields no results. Much of the work on the topic of fairness and machine learning (ML) has focused on longstanding challenges surrounding algorithmic fairness (Hellman 2020), de-biasing word embeddings (Sun et al. 2019; Badilla, Bravo-Marquez, and Pérez 2020), the use of counterfactuals (Corbett-Davies and Goel 2018; Chouldechova and Roth 2020), and problems associated with under representative data sets (Du et al. 2020).

On the associated topic of morality, a number of papers have investigated the use of Moral Foundation Theory (MFT) (Graham et al. 2013) to analyse texts. MFT uses six foundations to parsimoniously explain the origins of human
moral reasoning. These are Care/Harm, Fairness/Cheating, Loyalty/Betrayal, Authority/Subversion, Sanctity/Degradation, and Liberty/Oppression. The general approach has been to label a dataset of texts with these categories, and then apply a ML algorithm, e.g., long short-term memory (LSTM), support-vector machines (SVM), to learn the distinctions between each category (Rezapour, Shah, and Diesner 2019; Hoover et al. 2020; Rezapour, Dinh, and Diesner 2021). A similar approach has also been used based on pre-defined measures of moral language (Pennebaker, Francis, and Booth 2001; Araque, Gatti, and Kalimeri 2020). These approaches have proved useful as a form of topic modelling of language, yet they are unable to mark a sentence as being fair or unfair, or offer a degree of explainability as to why a classification was made, and to what degree each sentence is fair or unfair. Indeed a common challenge to ML systems of this type is that of limitations imposed by the technology on explainability (Danilevsky et al. 2020). This also presents a problem in work done using black-box ML to class documents as belonging to legally fair or unfair categories based on pre-trained legal clauses (Ruggeri et al. 2021; Lagioia et al. 2019). Their approach does not seek to identify explainable factors behind why something is perceived as fair or unfair, but instead, accept it as given that certain legal clauses are fair and others unfair, for which they implement ML methods to draw a classification boundary. Testing their API (“CLAUDETTE” 2021) with the sentence ‘the boy will hit the girl’, for example, produces the result: ‘Claudette found no potentially unfair clause’. Which may be a reflection of out-of-domain knowledge limitations.

Work done by (Schramowski et al. 2019) and (Jentzsch et al. 2019) have demonstrated that language models (LM) such as Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019) hold implicit representations of moral values. They do so using vector comparisons based on a template of Do’s and Don’ts. Furthermore (Schramowski et al. 2019) replicates the moral choices found by (Jentzsch et al. 2019), then computes the variance explained by another LM, the Universal Sentence Encoder (USE) (Cer et al. 2018) with respect to Yes/No question templates on moral choices. Further work in (Izzidien 2021) replicates the finding that word embeddings contain implicit biases, and proposes to use them to make assessments of verbs.

Building on these studies, we propose to harness these implicit social biases to act as a metric for an explainable assessment of sentences, specifically those related to fairness. However, in order to extract this bias, and instead of using a template of Do’s and Don’ts, we build on work in the social psychology literature on determining, which factors are able to explain acts of fairness made by humans, from which we extract a template that represents the principal perceptions, humans typically engage when making a fairness assessment. In doing so, we aim to approximate those perceptions, which we hypothesise will allow sentences to be classed according to which perception they are closer to, being fair or unfair.

Although the paper does not set out to produce a fully validated and verified fairness measurement tool, it contributes to the development of one based on an approximation of the factors, humans engage when making such measurements. In effect, the metric may be considered a proxy for fairness perceptions. As such, we do not claim to be measuring a specific fairness type, e.g., distributional/outcome. However, as will be discussed, fairness evaluations engage a number of principal psychological factors. It is these factors that we attempt to approximate using a method of word embeddings. While the ML techniques used in this paper are well established, our approach to digitising the factors, and the theory behind their use in this domain is new. Not least as no such measure exists in the literature.

The paper is organised as follows. The methods section is presented next, this incorporates a detailed study to determine the most explanatory psychological factors present in fairness assessments. The paper then details two approaches
to digitise these psychological factors using word embeddings and ML. The results are then presented. A short discussion is followed by improvements, limitations, and the conclusion.

This paper contributes originally with the following:

1) A new literature review to determine the principal factors that best explain pro-social acts, employing the dictator game (DG) to remove the confound of strategic intentions – i.e., where a pro-social act is engaged not out of fairness, but due to fear of punishment.

2) The use of the factors found in the above literature review to act as measures in multidimensional vector space. We implement an under-utilised method of vector linear algebra to define an ontological approximation of fairness perceptions.

3) The use of the above vectors as a measure of test sentences; are they closer to being: *fair*, or *unfair*, and to what degree?

**Methods**

To be able to characterise the factors that humans use when making a fairness assessment, we turn to the psychology literature. Using controlled experiments, neuro and social psychologists have considered what factors best explain pro-social acts such as fairness. These studies have involved between-subjects trials, survey questions, psychometric testing and experimental variable manipulations as detailed next.

**The Psychological Factors**

One of the challenges of exploring, which traits positively predict people acting fairly, is that social interactions often involve feedback between individuals. Thus, asking a participant to share part of a resource with another introduces many confounds, such as social desirability (Platow 1994), and possible expectations of reciprocity to include reward and sanction (Fehr and Gächter 2000). To address this problem, a number of psychologists have attempted to isolate factors that predict prosocial acts by modelling a scenario, in which an actor has the choice to share without any concern for the repercussions of withholding. This has taken the form of the Dictator Game (DG) (Guala and Mittone 2010).

A DG allows a person to choose, how much of a resource to share with another person, without any concern of being punished, allowing for the removal of strategic intentions (Ibbotson 2014). A person is typically presented with a pot of cash, which they may keep in its entirety. They may also share part or all of the cash with another player, or several players. The context and frame of the study is often manipulated by the researcher to attempt to decipher, which factors influence how much is given. Spanning 25 years, and 20,813 trials, incorporating 24 factors to overcome the limitations of
single studies, a meta study by (Engel 2011) was conducted on these games. They determined that outside of age the strongest positive effects for two person DGs concerned the two variables of recipient need and legitimacy.

Using the effect sizes (marginal effects) from the meta-analysis as the true population effect size, a second meta-analysis (Ortman and Zhang 2013) calculated the post-hoc statistical power for the studies included in Engel’s meta-study—which investigate at least one of those explanatory variables by the non-central $t$ distribution. They found the effect size for deserving recipient was 1 for four of the studies and above 0.6 for the fifth. Recipient earned was under 0.2, dictator earned was close to 0.6 for eleven studies. Outside of a framing effect (Zhang and Ortmann 2014) also replicates (Engel 2011).

Given that these two factors, legitimacy and need, were two main psychological contributors to giving, many of the individual studies that found this effect were characterized by their use of the language of need, deservedness and entitlement (Cappelen et al. 2013). A study using the frame: “Note that he relies on you” found that selfish behaviour in the DG almost vanished (Brañas-Garza 2007). Further, a strong effect was observable that was independent of the extent of altruism measured or of the dictator being seen (Rodrigues, Ulrich, and Hewig 2015).

A perception of fairness was demonstrated as being modulated by an integration of the two factors of egalitarian motivation and that of entitlement (Feng et al. 2013). On entitlement effects, acts of giving were found due to the sense of earned shares as evocative of a right that they deserve (Cappelen, Sørensen, and Tungodden 2010). Such entitlement frames have also been used to explain the observation that individuals in such contexts do not share more of their earned income with those in greater need (Eckel and Grossman 1996).

It is the position of this paper that the language encompassing need and entitlement is evocative of two social values: a right e.g., he worked for it, and a responsibility to help: e.g., he relies on you. Both rights and responsibilities may be considered opposite sides to the same coin: If someone has the right to something, then someone else has a duty towards that person with respect to that right. As such, responsibility is considered concomitant to a right, as is well established legal philosophy (Kramer 2000).

Using 150 observations (Tisserand, Cochard, and Le Gallo 2015) analysed the two person DGs across seventy papers (1986 to 2014). Their comparative pooled meta-analysis revealed that dictators from countries low in industrialisation exhibited greater considerations for fairness. It was found that the level of industrialization had a strong negative and significant influence on share. Players from industrialized countries shared significantly less, 11.41%. This finding being confirmed in Engel (2011) who found that with indigenous countries, the proposer gives more. Such may be reflective of the characteristic of responsibility, which studies report to be influenced by the cultural climate of the person: In a 40 years longitudinal cohort, responsibility was at its lowest when a culture of individualism was at its peak (Helson, Jones, and Kwan 2002; Jensen-Campbell, Knack, and Rex-Lear 2009; Tisserand, Cochard, and Le Gallo 2015). Indeed a study (Handgraaf et al. 2008) that specifically manipulated the DG to account for mediation effects found that the trait of social responsibility was the best predictor of giving.

Given this factor, we turned to the wider literature to consider studies that specifically controlled for responsibility in their manipulations. These studies were also found to replicate the above finding. (van Dijk and Vermunt 2000) used 96 participants, and asked them as to the extent they considered it was their responsibility to share the money fairly. They found the unilateral power distribution in the DG triggered a social responsibility norm. The paper found a main effect that
those in the DG condition (M=55.6) felt more strongly they ought to share their money fairly than did those taking part in the Ultimatum Game setting (M=54.9), 2 × 2 ANOVA (F(1, 87)=54.1 (p <0.05)). A study by (Yang et al. 2020), n=95, considered the Sense of Community Responsibility (SOC-R) and its association with altruism behaviour (AB). They found a positive correlation between the two (r = 0.47, p < 0.001), with monetary share being significantly different between a split of two groups, one with a low SOC-R, and one with a high SOC-R (t (51) = 3.50, p < 0.01, Cohen’s d = 0.72). Their regressions demonstrated a linear relationship between AB and SOC-R (F (1, 93) = 26.86, p < 0.001), with SOC-R as the predictor and AB as outcome. The Sense of Community Responsibility measure was found to explain 22.4% of the variability in the AB (R^2 = 0.224). (Brañas-Garza, Durán, and Paz Espinosa 2009) found that factors of personal involvement and responsibility were able to explain the reasons behind why positive values were given in DGs.

(Sijing and Jianhong 2011) used a DG and Third-Party Game (TPG) to activate the social norm of fairness. They found social responsibility had a critical role in norm activation. Players who scored higher on social responsibility were characterized with greater pro-social behaviour after being activated. A study by Milgram determined that when one was able to make another person responsible for an act, anti-social acts could more easily materialise. Concordantly, (Cui et al. 2015) reports that the activations of a person to witnessing others in pain is modulated by the witnessing parties responsibility, whereby responsibility sharing, or not being responsible, lowers the pain-matrix neural activity.

One method to attempt to falsify the claim that responsibility has the theorised effect on a person, would be to remove or diminish it. A number of studies attempted this manipulation. These are detailed next.

In the study by (Dana, Weber, and Kuang 2007), participants undertook a modified DG with a binary choice between an equal and an unequal allocation of wealth. The design used a baseline and three treatments, n= 190: baseline, hidden information, multiple dictators, and plausible deniability. In the baseline most of the dictators gave fairly (74%). In the hidden payoffs however, of the sixteen dictators who confronted the same payoffs as in the baseline ten (63%) chose the option that gave them the most gain with an obfuscation of transparency (χ^2(1) = 4.64, p = 0.03). While 74% selected the fair choice for the baseline, this reduced to 35% when two dictators were present (χ^2(1) = 5.87, p = 0.02). For the final study, 10 out of 29 choices made (34%) were consistent with a wish to execute a fair result. They find that the contrast in the allocation share between non-transparent and baseline conditions, indicates behaviour that is contextually driven. As such, both preferences for fair and self-interest outcomes can become apparent, ones that are dependent on the said context observed by the allocator in the game. A limitation was that a scoring of the dictator’s social responsibility would have addressed whether those who opted for less transparency had done so due to a low responsibility score. It appears though that the factor of responsibility itself was a determining factor in their behaviour. Also missing from the study was whether the situational frame was construed as one that demanded a responsibility assessment, or not.

In the study by (Karni, Salmon, and Sopher 2008), they consider the willingness of a player to give up their own chance of winning in order to arrive at what is perceived as a fairer allocation procedure, n=135, in a three-person DG. An apparent strength for fairness preferences, while still present, is found to decrease below 20%, from which they consider that it may be the social distance or concern of not appearing unfair to others that drives the decision, the latter effectively confirming the results by (Dana, Weber, and Kuang 2007) above. Limitations wise, while the study manipulation did ask
participants to choose what they deemed fair, it did not evaluate whether the context was perceived as one that demanded a fairness evaluation by the players.

A study by (Cryder and Loewenstein 2012) considered whether individuals were more generous in two player DGs than in conditions for which responsibility for any one receiver is potentially divided across more than one dictator. The paper used a between-subjects design: (Decision Recipient: Not Determined, Determined) × 2 (Decision Maker: Not Responsible, Responsible), n=250. They found that when an individual was completely responsible for somebody else's outcome, the chances of giving rose by a factor of 3.03 ($\chi^2 = (df=1, N=80) = 5.58, p < 0.02$). They determined that unambiguous responsibility for a single receiver leads to a higher share. A second manipulation, n=296, considered the responsibility effect using a shopping area, one of four conditions was set to elicit a sense of responsibility. Participants who were solely responsible for the outcome of another individual were found to be significantly more generous. They highlight the possibility of a bystander effect, and social desirability. A limitation of this study was that there was no direct measure of responsibility or context. In (Hamman, Loewenstein, and Weber 2010) the group considered whether the use of delegates in economic settings leads to settings in which the accountability for questionable moral decisions becomes vertically diffused, whereby no single person is seen as responsible for the outcome. Nineteen sessions were conducted, n=264. The study used a questionnaire to ascertain the level of responsibility and fairness of action carried out, but no questions on the perception of the frame was made. Conditions in which agents were pooled (Agent and Agent choice) resulted in significantly less feelings of responsibility for the amount shared compared to their baseline DG condition. The proposer's sense of responsibility was highly influenced by the condition used in the study. Dictators generally preferred to use agents, and this act of delegation led to highly reduced amounts being shared with others.

The indirect assessment of responsibility was made by (Bartling and Fischbacher 2012), n=952 (aggregated). In their manipulation they used a 'punishment assignment' for the results of decisions that were delegated, interpreting such as a measure of responsibility attribution. They found that a measure of responsibility outperformed measures that used inequity aversion or reciprocity to predict punishment behaviour: the predictive power of the outcome motive was ($R^2 = 0.21$) being the lowest, while an intention motive was ($R^2 = 0.29$), and the outcome and intention interaction was higher ($R^2 = 0.37$), whereas the responsibility motive was highest ($R^2 = 0.42$). No direct measure of the situation as eliciting a sense of responsibility was given.

Lastly, a gift-exchange study (Charness 1998) found that participants respond with more generosity when a wage is determined by a process that is random than when such is assigned by a third party. Such a shift, albeit small, in perceived responsibility for the final pay was found to alter behaviour. Participants felt less of an impulse to contribute ($\chi^2 = 20.6, df = 9$) to an anonymous employer when they perceived that a third party had approved the wage in some way resulting in a shift of some responsibility for the determination of the outcome. They found that individuals are in general more generous with anonymous strangers when they must assume full responsibility for payoff allocation.

Contingent Factors

When a human perceives a context as one that warrants a social responsibility evaluation (Handgraaf et al. 2008), such evaluation is dependent on constituent factors. By constituent factors, we mean the minimum factors needed to allow
for a perception of responsibility to materialise. Intuitively, these are a perception of the frame (Engel 2011; Zhang and Ortmann 2014) in terms of:

1) The benefit-harm gained: A measure of how the actors actions will result in a benefit to the receiver or lack thereof (Brañas-Garza et al. 2014; Perera, Canic, and Ludvig 2016; Bruner and Kopec 2018; Chiaravutthi 2019).

2) The consideration of public benefit and harm (Sigmund, Hauert, and Nowak 2001; Gillet, Schram, and Sonnemans 2009; Lejano and Ingram 2012).

3) The emotional salience of the context: how much joy-pain is involved (Batson et al. 1991; Scheres and Sanfey 2006; Tabibnia and Lieberman 2007; Edele, Dziobek, and Keller 2013).

4) Outside the DG, a further perception of the possible consequences is incorporated: rewards and punishments (Nesse 1990; El Mouden et al. 2012, 24; Boyd et al. 2003; Scheres and Sanfey 2006; Henrich et al. 2001; Bartling and Fischbacher 2012; Strang and Park 2017).

These factors interact in a social context, allowing for a pro-social human propensity to materialise, termed the ultra-cooperative trait, and seen as unique to human society (Nowak 2006) (Tomasello 2014).

It may be hypothesized that such a social propensity is reflected in human discourse. Indeed, the use of language has been shown to reflect social perspectives (Kennedy et al. 2021).

It has also been shown that a variety of biases found in the usage of language can be measured when they are used in word embeddings. This is a method by which words are no longer defined by their entry in the dictionary, but by their co-occurrence with other words (Pennington, Socher, and Manning 2014). Social biases, such as the association of an ethnicity with a trait, become more pronounced due to such association (Garg et al. 2018). Given a human propensity for receiving pro-social acts, and its articulation in general discourse, such a pro-social bias may also present in word embeddings, where certain types of social interactions are associated with praiseworthy terms, while others are associated with blameworthy terms, such as fair and unfair acts respectively. We detail this next.

**Word Embeddings as Measures**

**Approach 1**

One of the most pertinent features of word embeddings are their mathematical properties (Pennington, Socher, and Manning 2014). Words become represented based on their co-occurrences with other words, often captured by the saying ‘you shall know a word by the company it keeps!’ (Firth 1958; Nerbonne and Hinrichs 2006). Embedded words are represented by vectors, which can be added, subtracted and compared. A commonly cited example is that of manipulating a vector which represents the word ‘king’. In subtracting the vector for ‘man’ from it, then adding the vector for ‘woman’ from it, the result in vector space approximately equals the vector representation for the word ‘queen’.
removing the representation of the word for ‘man’ from the vector for ‘king’, produces a vector that remains representative of the quality of royalty. By adding the vector representation of ‘woman’, the new vector represents a more feminine form of royalty, or in this case, the word ‘queen’ (Pennington, Socher, and Manning 2014; Drozd, Gladkova, and Matsuoka 2016).

Vectors can also be compared to each other using cosine similarity. Where closely associated vectors score closer to +1, and less associated vectors closer to -1. Using these straightforward methods, it becomes possible to consider how similar vectorised sentences are (Kozlowski, Taddy, and Evans 2019).

Furthermore, word embedding has been found to incorporate more than semantic information, indeed other social dimensions represented in language have been found to be captured. Such as demographic features (Kozlowski, Taddy, and Evans 2019) and ethic and gender biases (Garg et al. 2018) as mentioned.

Given that language reflects the social values of its speakers (Smith 2010; Kennedy et al. 2021), we hypothesize that word embeddings will reflect the social propensities determined by the psychology literature. Thus, sentences that describe fair acts will be more closely associated with sentences that describe responsibility, benefit, joy, and reward, than that of their antithesis terms of irresponsibility, harm, sadness, and punishment. Based on this, it becomes potentially possible to use this feature, this pro-social bias, as a metric. Acts that are typically hurtful will co-occur more with negative social evaluations in typical corpora, reflecting the human propensity towards pro-social acts. As such it may become possible to leverage this bias as a metric.

To use embeddings for this purpose, we propose a little used method of adding and subtracting vectors (Foley and Kalita 2016) for the purpose of narrowing the implicit ontological associations of the resulting vector. Technically, embeddings reflect ontological properties because this ontology helps the models to decrease the perplexity of the corpus, i.e., better predict what words should appear in what context. In using word embeddings, built without any explicit ontological labels, the vector representation of the corpus implicitly reflect ontological knowledge (Erk 2012; Bhatia 2017; Runck et al. 2019; Racharak 2021). For example, grammatical ontologies become reflected due to the co-occurrence of specific grammatical knowledge in the co-occurrence of words (Qian, Qiu, and Huang 2016). The term fairness, being a collection of several social ontologies may be nominally represented using vectors, through the addition and subtraction of vectors which represent those factors found in the above psychology literature. We use this assumption to ‘triangulate’ a term by outlying its main ontologies. Thus, similar to how a Venn diagram intersects at a mid-point, we add and subtract the vectors that represent sentences carrying a nominal meaning of the principal factors. In effect, we attempt to incorporate latent vector representations resulting from such addition and subtraction. We detail our method next.

The Vectors

To represent the psychological factors as vectors, we constructed the following sentences that describe them (table 1), which we then converted into vector format using the USE (Cer et al. 2018). Notation wise, and for the purposes of this paper, a sentence is represented with a lower-case letter, and its vector space embedding by that letter with an arrow on top. For instance, the sentence \( v = "it was irresponsible" \). Its vector space embedding will be written as \( \vec{v} \). In cases where no
letter is assigned to a sentence, the vector embedding of a sentence is designated by placing an arrow on top of the sentence. For instance, it was very irresponsible.

The wording of the sentences were induced from each of the above numbered lists, thus, the two opposite terms of benefit-harm (Brañas-Garza et al. 2014; Perera, Canic, and Ludvig 2016; Bruner and Kopec 2018; Chiaravutthi 2019) were constructed into: "it was beneficial" − "it was harmful". In considering public benefit-harm (Sigmund, Hauert, and Nowak 2001; Gillet, Schram, and Sonnemans 2009; Lejano and Ingram 2012), we constructed: "it was beneficial to society" − "it was not beneficial to society". For the emotional salience of the context, i.e., how much joy-pain is involved (Batson et al. 1991; Scheres and Sanfey 2006; Tabibnia and Lieberman 2007; Edele, Dziobek, and Keller 2013), the sentence constructed was "it was joyous" − "it was sad". Given that outside of a DG, the factors of reward and punishment are contingent factors (Nesse 1990; El Mouden et al. 2012, 24; Boyd et al. 2003; Scheres and Sanfey 2006; Henrich et al. 2001; Bartling and Fischbacher 2012; Strang and Park 2017), the following sentences were used: "was free to and rewarded" − "was sent to prison and punished". For this vector, we used two opposite terms to each side of the scale to reflect both the material and abstract nature of the consequence, i.e., prison vs. being free (material), and punished vs. rewarded (abstract). Lastly, the main explanatory factor of the literature ‘responsibility’ was framed: "it was very responsible" − "it was very irresponsible" and given that the quality of ‘responsibility’ was the most pertinent factor, we expressed it with the term ‘very’ to maximise the range as a means to reflect it. Other words such as ‘incredibly’ could also have been used given that similar words occupy similar regions in vector space (Erk 2012). We also found that using directly opposite senses of a word such as responsible vs. irresistible vs not responsible offered slightly varying results – which we detail in the limitations. In selecting which wording to use, we focused on the abstraction of the factor. As such other wordings are possible, so long as they represent the same abstract meaning of the factor they represent. This is based on the knowledge that locations within vectors spaces are similar for similar meanings (Erk 2012).

The wordings used are given in table 1.

| Factor                      | Wording for scale                                           |
|-----------------------------|-------------------------------------------------------------|
| Responsibility dimension    | it was very responsible - it was very irresponsible          |
| Emotional dimension         | it was joyous - it was sad                                  |
| Public benefit dimension    | it was beneficial to society - it was not beneficial to society |
| Personal benefit dimension  | it was beneficial - it was harmful                           |
| Consequence dimension       | was free \∧ rewarded − was sent prison \∧ punished           |

Table 1. Using the psychological factors and contingent factors for vector wordings
The vectors were constructed:

\[ \hat{v}^{(1)} = \text{"it was very responsible"} - \text{"it was very irresponsible"} \]

\[ \hat{v}^{(2)} = \text{"it was joyous"} - \text{"it was sad"} \]

\[ \hat{v}^{(3)} = \text{"it was beneficial to society"} - \text{"it was not beneficial to society"} \]

\[ \hat{v}^{(4)} = \text{"was free to and rewarded"} - \text{"was sent to prison and punished"} \]

\[ \hat{v}^{(5)} = \text{"it was beneficial"} - \text{"it was harmful"} \]

The linear arithmetic allows for a capture of a range, going from positive to negative. Thus, if we consider the vector describing \text{"it was beneficial"} - \text{"it was harmful"}, and compared it to a vectorised test sentence, such as \text{"the guard helped the man"}, through a cosine similarity calculation, the result will be a score from +1 to -1. The more associated the sentence is with benefit, the closer to 1 will be the result. Whereas sentences that are more associated with harmfulness will provide an outcome closer to -1.

The sentence level fairness perception measure vector \( \hat{v} \) is made by combining the vectors above:

\[ \hat{v} = \hat{v}^{(1)} + \hat{v}^{(2)} + \hat{v}^{(3)} + \hat{v}^{(4)} + \hat{v}^{(5)} \]

We refer to this as the fairness vector, notwithstanding the limitations described earlier. In using this result, it becomes possible to compare \( \hat{v} \) to the embedding of a test sentence, e.g., “the boy hit the baby” to determine how close the test sentence is in vector space to the parsimonious representations of fairness, by computing the cosine similarity.

In performing the linear manipulation – the addition and subtraction of vectors, the new vector \( \hat{v} \) is able to capture a scale. One that allows for a comparison of a combination of these social dimensions to the sentence being tested.

Were it the case that only one of these social dimensions be used with a test sentence, the result would expectantly not capture the minimum pertinent factors associated with a perception of fairness. To demonstrate this, the results of using each factor \( \hat{v}^{(1)} \hat{v}^{(5)} \) are plot in the results section for comparison. For which a random selection of sentences from the pre-
prepared 200 sentences is used for illustration purposes. The 200 sentences were compiled by three independent contributors.

A test is also conducted to compare the result of using such a parsimonious representation of fairness $\vec{v}$, with a straightforward vector embedding $\vec{v}^f$:

$$
\vec{v}^f = \overline{\text{"it was fair"}} - \overline{\text{"it was unfair"}}
$$

It may be hypothesised that such a vector $\vec{v}^f$ will reflect a sum of variations on how the term ‘fair’ and ‘unfair’ is used in a corpus. Given the variation of definitions, it would be expected that such a representation would produce conflicting results. This contrasts with building up an ontology of fairness using representations commonly exhibited by humans as determined in the social psychology review above. The results are discussed later in the section on the results found in using the two different methods, with and without psychological ontologies associated with fairness.

To consider whether the use of the fairness vector $\vec{v}$ is simply replicating a sentiment analyser, we perform a sentiment analysis using Vader (Hutto, 2021) against the 200 test sentences and correlate the result with the result of using the fairness vector $\vec{v}$ against the same test sentences.

**Approach 2**

While adding and subtracting vectors offers a potential method to encompass fairness perceptions into a single vector, some information is inevitably lost by such a reduction. As an alternative we preserve the vectors for each of the evaluations, each as separate dimensions.

As such, we do not perform the above addition of $\vec{v}^{(1)} + \vec{v}^{(2)} + \vec{v}^{(3)} + \vec{v}^{(4)} + \vec{v}^{(5)}$, but rather use each independently. Thus, to evaluate a test sentence, e.g., “the shopkeeper assisted the customer”, its word embedding vector $\vec{s}$ is compared, through cosine similarity, with the each of the five vectors $\vec{v}^{(1)}$ to $\vec{v}^{(5)}$, the results of which are stored in a multi-dimensional vector $\vec{v}^m$. For example, supposing the result of such a cosine similarity operation were:

$$(\vec{v}^{(1)}, \vec{s}) = 0.2$$
$$(\vec{v}^{(2)}, \vec{s}) = 0.1$$
$$(\vec{v}^{(3)}, \vec{s}) = 0.6$$
$$(\vec{v}^{(4)}, \vec{s}) = 0.3$$
$$(\vec{v}^{(5)}, \vec{s}) = 0.2$$
The stored result $\vec{v}^m = [0.2, 0.1, 0.6, 0.3, 0.2]$

This is repeated for all 200 test sentences, resulting in a dataset D1, which is then hand labelled with the correct fairness assessment (table 2):

| Index | Test sentence                      | Result ($\vec{v}$ | $|m|$) | Label |
|-------|------------------------------------|-------------------|---------|-------|
| 1     | the shopkeeper assisted the customer | $[0.2, 0.1, 0.6, 0.3, 0.2]$ | Fair    |
| ...   | ...                                | ...               | ...     |
| 200   | the prisoner murdered the inmate    | $[-0.4, -0.6, -0.3, -0.3, -0.4]$ | Unfair  |

Table. 2 Snippet of dataset D1.

This produces a dataset containing the multidimensional vector and its label.

To explore how the factors induced from the psychology literature explain the data, a principal component analysis (PCA) is performed, initially with two components, then three.

To use the Dataset D1 for training a classifier, we perform ML using a logistic regression classifier, and a 1:7 test split.

To encode all the sentences used in this paper, we use the universal sentence encoder (Cer et al. 2018), which we detail next.

**The Universal Sentence Encoder**

Initially shallow pre-training of early model layers became standard in NLP research through methods such as Word2vec (Mikolov et al. 2013). Subsequent progress followed trends similar to those in computer vision, which naturally led to pre-training of multiple layers of abstraction. These advancements resulted in progressively deeper hierarchical language representations, such as those derived using self-attention mechanisms in transformer-based architectures (Vaswani et al. 2017). Currently state-of-the-art NLP systems use representations derived from pre-training of entire language models on large quantities of raw text, and often involve billions of parameters. The success of neural network-based ML models, especially those involving very deep architectures, can be attributed to their ability to derive informative embeddings of raw data into submanifolds of real vector spaces. The common idea behind these developments is that we can learn syntax and semantics of natural languages by training a Deep Learning (DL) model in a self-supervised fashion on a corpus of raw text. Modern embedding methods combine word and sub-word (e.g., morpheme or character) level
embeddings in a hierarchical and contextualized fashion to produce sentence and document level representations into (usually high-dimensional) submanifolds of \( \mathbb{R}^n \).

Traditionally, such coarser representation methods combined token-level embeddings by mapping them to a single vector through a variety of models (e.g. vector averaging and word2vec inspired methods (Arora, Liang, and Ma 2016) (Chen 2017) (Hill, Cho, and Korhonen 2016); (Kenter, Borisov, and De Rijke 2016) (Kiros et al. 2015) (Le and Mikolov 2014) (Logeswaran and Lee 2018) (Pagliardini, Gupta, and Jaggi 2017), attention mechanisms (Radford et al. 2018; Reimers and Gurevych 2019; Devlin et al. 2019) convolutional architectures (Liu, Zhao, and Volkovs 2017), or gated recurrent units (Hochreiter and Schmidhuber 1997; Cho et al. 2014).

One popular model for deriving general purpose sentence embeddings for downstream NLP tasks is the USE (Cer et al. 2018), which outperforms traditional sparse word transfer models that existed at time of its introduction.

Given the high costs and low availability of manually labelled texts for training NLP models, word transfer models deploy pre-trained word embeddings (Mikolov et al. 2013; Pennington, Socher, and Manning 2014), which were successfully adapted to sentence-level representations (Conneau et al. 2017), and in particular utilised within the encoding module of the USE.

The USE introduces two embedding modules, one based on transformer sentence encoding providing high accuracy, and one deploying a deep averaging network (DAN), which focuses on computational efficiency.

This combination of features presented by the USE made it a good choice for our work. The reasons for this choice are two-fold. First, the mixture of deep self-attention induced encoding with the simpler DAN module, make it somewhat a compromise between predictive power and computational efficiency. Second, it marks a midpoint between sparser and more explainable models and deeper black-box architectures. This trade between explainability and accuracy is especially useful in the context of our work. Shallow models are closer to typical statistical learning and analysis procedures, which are prevalent in psychology and social sciences today, which make them ideal to study the ramifications of defining model components based on psychological theory, and prepare the ground for further theory driven research at the intersection of NLP and ethics.

Since the transformer side of the USE allows us to derive powerful context sensitive representations for natural language inputs, while on the other hand, the DAN side of USE allows us to inject these ethical considerations into the final representations of sentences produced by the combined encoder modules, it is particularly useful for work combining theory driven ethical considerations with natural language modelling methods. Our choice of USE as the primary sentence embedding method, allows us to impose knowledge derived from psychological findings that are based on social cognition and social neuroscience, which would be hard to do in a fully unsupervised setting. This has the further benefit of combining transparency and efficiency, which is important to the type of work presented in this paper.

On a technical level, the USE first transforms languages to lower-case and tokenizes them via the PennTreebank (PTB) (Taylor, Marcus, and Santorini 2003). In both variants, a 512-dimensional embedding is produced. The transformer encoder deploys sub-graph encoding (Vaswani et al. 2017) to create sentence embeddings through a six-layered stack, whereby at each layer, a self-attention mechanism is followed by a feed-forward network. Words are fed through these layers, and their order as well as their context is taken into account through the use of positional embedding and sentence
level attention mechanism. This process iteratively enriches representation of each word in order to augment the resulting embedding with contextual information of the sentence in which it appears within the corpus.

Each embedding is then added together, whereby the length difference of sentences is ‘standardised’ by dividing through the square root of the length. This results in an output sentence embedding in shape of a 512-dimensional vector, which is then fed into various downstream tasks. The DAN variant is based on deep averaging networks (Iyyer et al. 2015) and follows a simpler approach, which starts by averaging embeddings for both bi-grams and words, and then passing these through a four-layered neural network output module.

To ensure general purpose deploy-ability, the transformer encoding deploys multi-task learning, whereby one input model is fed into several downstream tasks. First, unsupervised learning is achieved through a Skip-Thought resembling task, replacing the encoder by the above two variants of input models (Kiros et al. 2015). Second, input-response task for parsed conversational data, which deploys the same encoder for input and output to model the difference of both, whereby their dot product determines the respective relevance, and it is fed through a softmax function, resulting in an optimisation over log likelihood of obtaining the correct response (Henderson 2017).

Last is the classification task using sentence pairs that represented the premises, hypotheses, and judgements about each pair. Such are fed through the transformer and DAN encoders described above, resulting in two 512-dimensional embeddings, processed by fully connected layers and three-way softmax, resulting in the probability of a judgement for each pair, which resembles earlier approaches (Conneau et al. 2017) to the task of natural language inference.

\[
sim(\vec{u}, \vec{v}) = \left(1 - \frac{\arccos\left(\frac{\vec{u} \cdot \vec{v}}{||\vec{u}|| \cdot ||\vec{v}||}\right)}{\pi}\right) \quad \text{Equ. 1.}
\]

Finally, for classification transfer tasks, the respective outputs are fed into a specific deep neural network, whereas for the pairwise similarity task, the similarity is calculated in the following way:

First, the cosine similarity of two sentence embeddings coming from the two encoders is computed, then, the angular distance is obtained by applying the \textit{arccos} function (Equ. 1) to the normalized inner product of the corresponding sentence representations.

**Results**

**Approach 1:**

In considering a list of 36 sentences (Appendix 1) selected randomly for illustration purposes from the list of 200 sentences, each test sentence is compared through a cosine similarity with the vector:
\[ \vec{v} = \vec{x}_{0000 \_wasfair} - \vec{x}_{0000 \_wasunfair} \]

**Fig. 1** Incorrectly classed sentences. All sentences of the left of the dotted line ought to be positive, while all sentences on the right ought to be negative. The incongruence of the scoring of the unfair sentences on the right can also be seen by comparing the score for murder (-0.024) to that of the act of misinforming (-0.087).

As can be seen from this illustrative example, thirteen of the sentences are misclassified (figure 1). Even correctly classified unfair sentences are classed in a manner that does not necessarily reflect typical evaluations: ‘The man sickened the lady’ is classed as closer to ‘it was unfair’ than the sentence ‘the father murdered the boy’ by many orders of magnitude.

If on the other hand the metric used to measure the sentences was built up using the aforementioned ontology of fairness perceptions, the results reflect more typically associated allocations. As a means to demonstrate how each of the ontologies gives separate results when they are used signally, figure 2 is plot, representing the outcome for using each of the five vectors: \( \vec{v}^{(1)} \vec{v}^{(5)} \).
In figure 2a, for example, reflects how similar each sentence is with the phrase: "it was responsible" - "it was irresponsible". Six unfair sentences are misclassified as responsible.

Each cosine similarity outcome is plotted with each of the illustrative sentences (fig. 2a to 2e). Here we observe how each sentence score is a reflection of factors contained within the corpus. For example, most of the test sentences describing fair acts, are classed as having a negative consequence (figure 2c).
To minimise this form of noise we linearly combine the vectors. Adding and subtracting them all into the fairness perception single vector, $\vec{v} = \vec{v}^{(1)} + \vec{v}^{(2)} + \vec{v}^{(3)} + \vec{v}^{(4)} + \vec{v}^{(5)}$ and repeat the cosine similarity calculation. This produces fig. 3, for which we find a more typical reflection of fairness perceptions is obtainable, though not perfectly accurate.
Fig 3. S-FairVec more closely reflects typical fairness perceptions of acts.

The above examples use 18 fair and 18 unfair illustrative sentences, for a more rigorous test, we using the fairness vector $\vec{v}$ with the full list of 200 sentences (Appendix 2), which we find produces an $F1= 81.0$, compared to an $F1= 55.2$ for using $\vec{v}^f = \sum_{x=0}^{000} \text{if wasfair} - \sum_{x=0}^{000} \text{if wasunfair}$ (figure 4) and (table 3).

| N=200 | Vector used | Vector used | Actual Class | Actual Class |
|-------|-------------|-------------|--------------|--------------|
|       | $\vec{v}^f$ | $\vec{v}$   | Fair         | Unfair       |
|       | Fair        | 45          | 18           | 74           | 9            |
|       | Unfair      | 55          | 72           | 26           | 81           |

Table 3. Confusion matrix for testing both vectors $\vec{v}$ and $\vec{v}^f$ against the full list of sentences.
Fig 4. A visual comparison of using the vector $\tilde{v}^f$ for ‘it was fair – it was unfair’ (left panel) vs. the fairness perceptions vector $\tilde{v}$ (right panel) to a list of fair and unfair sentences. Sentences to the left of the dotted light ought to be positive, while those to the right of the dotted line ought to be negative. Higher accuracy is found for the fairness perceptions vector $\tilde{v}$ with almost all unfair acts correctly classed as detailed in the confusion matrix seen in table 3.

Performing a Sentiment Analysis on the Sentences

For illustrative purposes, we compare the sentiment scores for the sentences below (table 4) with the result found in using the fairness vector $\tilde{v}$. A correlation of sentiment score using Vader (Hutto, 2021) and fairness vectors score for all 200 sentences is then carried out thereafter and found to be 0.66, indicating that $\tilde{v}$, captures dimensions beyond that of sentiment.

| Sentence                                      | Negative | Neutral | Positive | Compound | Sentiment Outcome | Fairness Perceptions Vector $\tilde{v}$ | Fairness Vector Outcome |
|-----------------------------------------------|----------|---------|----------|----------|-------------------|----------------------------------------|------------------------|
| The jury convicted the innocent               | 0.000    | 0.625   | 0.375    | 0.3400   | Incorrect         | -0.168450                             | Correct                |
| The army executed the innocent                 | 0.000    | 0.625   | 0.375    | 0.3400   | Incorrect         | -0.232097                             | Correct                |
Table 4. Comparison of a number of uncorrelated results

Results from Approach 2:

The dataset D1 is built, containing the multidimensional vector $\vec{v}^m$. Whereby the result of each vector comparison is stored in a single matrix, e.g., $\vec{v}^m = [0.2, 0.1, 0.6, 0.3, 0.2]$. Each assessment is hand labelled as fair or unfair. The scatter plot for the dimensions can be seen below in figure 5.

Fig. 5. All dimensions using the vector $\vec{v}^m$ plot against each other using a scatter plot.

Performing a two component PCA on the dataset D1, figure 6:
**Fig. 6.** PCA on the 5 dimensioned data set, with an explained variance ratio of 0.56, 0.18, 0.15, 0.08, i.e., 74% explained in first two components.

Running a three component PCA, produces figure 7:

**Fig. 7.** three component PCA in three dimensions. The total explained variance being 88.53%.
Using a PCA, set for 95% of the variance, we then perform the ML step using a logistic regression classifier, with a test split of 1:7. The result is an F1= 86.2.

Discussion

In order for a vector to approximate how *fair* or *unfair* a sentence is, the terms used in the vector must reflect social ontological properties of fairness. That is, abstractions which make them more likely to be used and hence co-occur within a corpus with fair or unfair terms. While social rules and conventions differ between societies, the paper sought to leverage a higher abstraction of those social rules. Abstractions which we induced from the pro-social psychology literature.

While it may be objected that violence is also a trait that is manifest in societies, we argue in response, that while humans do harm each other, and while such acts will be reflected with a corpus, humans still would not wish the same violence upon themselves. That is, even someone stealing from another, would not want to be stolen from. Humans are typically averse to gainless activity. They prefer to be on the receiving end of pro-social and not anti-social acts, irrespective of culture.

This natural human bias, we have argued is held within corpora that contain typical human textual discourse – i.e., not fantasy and sci-fi novels where typical human social acts are morphed for dramatic effect, such as descriptions of societies where eating elderly gentlemen is a norm people regularly partake in with satisfaction and glee.

Arguing that these pro-social abstractions reflect when typical human discourse is vectorised using word embeddings, this paper sought to use these social factors as a metric.

Typically metrics are based on predefined conventions, which are reached though agreement, e.g., the length of a centimetre, or through deduction from survey data, such as the Big Five personality test (Raad and Perugini 2002). We have argued that it is possible to leverage the uniqueness of human language within multi-dimensional vector space, without the need of arranging for agreement on a fairness list of Do and Don’ts, for example. For the first approach used in this paper (approach 1) there was no need for ML training, which is atypical for a classification task, such as used in (Jentzsch et al. 2019). We used vector addition and subtraction to make a new vector that represents a range which incorporates a fairness perception. An incorporation makes the assumption that the new location in vector space is reflective of the implicit ontologies of its constituent word embeddings. In some sense this approach reflects a degree of what has been termed an onto-pragmatics approach (Dascal 1992), which has been suggested as method to simulate or understand cognition. Our approach may also be said to contrast with claims about the impossibility of appealing to cross-cultural values underlying human communication (Van Brakel 1991).

Furthermore, in using human readable vectors, the outcome has a degree of explainability, which has been seen as necessary for more ethical AI, and in incorporating principal factors, it is arguably able to capture elements of human context as described in vectorised corpora, an approach which has been wanting (Maclure 2021).

In the second approach (approach 2) we used the results obtainable from the fairness perceptions vector to train a ML algorithm. The latter approach improved classification (F1=86.2) compared to the former (F1=81.0). However, one advantage of the former approach is that, as mentioned, it offers an added explainability of its results. Since the classification of a sentence is based on known variables, which can be displayed to a user. Although the ML approach does improve on
these results, being based on more data points by virtue of using a multi-dimensional vector, a degree of explainability is lost.

It may be argued, that while ML was used in the second approach, it does offer a degree of explainability over other approaches that directly vectorise sentences and incorporate training labels. For example, Twitter data is often directly converted into vectors, with a label of their class. Thereby leaving the ML algorithm open to ‘choose’ which of the many social dimensions held in language will be used to make the classification. Offering no explainability for the ‘choices’ of the neural network. Whereas our approach, while also employing a ML algorithm, does so only after applying a form of filter to the vectorised sentences. That is, by selecting the specific dimensions we are interested in. This in turn may offer a way to ethically audit the pipeline using such a metric (Mökander and Floridi 2021).

While we used the psychology literature to find the principal factors that explain fair acts, it may be argued that the list of terms used is not exhaustive. Indeed, other factors do come into play, for example, ‘a feeling of guilt’ (Cartwright 2019). However, these factors are typically contingent on the principal factors outlined in the paper, i.e., a feeling of guilt cannot manifest if there has been no perception of the possible harm and loss. Or it was the case that these additional factors were shown to have less explainability of the variance in the social psychology literature (Engel 2011). Yet. It is still possible to add these as additional vectors to improve the measure.

Ideally, the wording of the terms used ought to be derived from the corpus itself instead of using human input as we have done. This is based on the premise that a social bias exists within the corpus, and that through an automated selective sampling of terms using a feedback loss mechanism, the most explanatory terms may be found for this bias within the corpus.

One of the contributions this paper makes, is that word embeddings can be thought of not only as reflecting semantic properties, but arguably, implied social propensities.

Further development of this metric is need to be able to offer a comprehensive measure of fairness, allowing it to exhibit a measure of a number of the ethical principles set out by the EU High-Level Expert Group on AI (Hleg 2019), specifically prevention of harm, fairness and explicability.

Yet, our approach of vector manipulation cannot capture the wholeness of a genuine and complete assessment of how fair or unfair a sentence is, due to a number of limitations, which we discuss next.

**Limitations and further work**

While the above vectors in \( \vec{v} \) are not fully linearly independent due to conceptual overlaps between the terms mentioned in each vector, we posit that despite this fact, when we add and subtract them, the concept becomes more restricted, similar to the central intersection point of a Venn Diagram - even if some of the circles overlap outside the central intersection. Indeed, achieving full linear independence in measures that have a psychological dimension may not be fully achievable. Using this combination arguably allows for more epistemic validity in defining fairness – in the limited sense used in the paper.
However, a more robust approach could be to use sub-space projections. Currently, we employ five vectors to construct a single vector \( \vec{v} \), which is then used to perform a linear analysis. We are also arguably losing an aspect of the ontology expressed in this constructed set of vectors by summing them into a single vector. Thus, if instead of summing the vectors, we can use them to form a basis for a subspace. We can then represent any other sentence vector in the ambient embedding space, by its projection onto that subspace.

While the multi-dimensioned vector \( \vec{v}^m \) components are linearly independent they are not orthonormal. To conduct a subspace projection, one would solve the system of linear equations to compute the correct coefficients.

If we define the subspace as \( \mathbb{C} \), the vectors can be used as a basis \( B = \{\vec{v}^{(1)}, \vec{v}^{(2)}, \vec{v}^{(3)}, \vec{v}^{(4)}, \vec{v}^{(5)}\} \) for \( \mathbb{C} \). Here any vector in the subspace will be a linear combination of the form:

\[
\vec{v} = \alpha \vec{v}^{(1)} + \beta \vec{v}^{(2)} + \gamma \vec{v}^{(3)} + \delta \vec{v}^{(4)} + \epsilon \vec{v}^{(5)}
\]

Instead of simply taking dot products with these vectors, a projection of any sentence in our model onto \( \mathbb{C} \), which is defined to be the linear span of \( B \), will be possible. As such, the vectors are used as a basis for the subspace. For example, a vectored test sentence \( \vec{t} \) can be represented as below, with \( \bar{\delta} \) being a factor that resides in the orthogonal complement of the subspace.

\[
\vec{t} = \alpha \vec{v}^{(1)} + \beta \vec{v}^{(2)} + \gamma \vec{v}^{(3)} + \delta \vec{v}^{(4)} + \epsilon \vec{v}^{(5)} + \bar{\delta}
\]

A computation to find the coefficients being possible through solving the system of linear equations obtained by taking inner products of each basis vector of \( \mathbb{C} \) with both sides of the above equation for \( \vec{t} \).

We could also encode an arbitrary projection onto the subspace with a matrix corresponding to this linear transformation, instead of solving systems of linear equations explicitly. Subsequently, we can perform a PCA, finding a separating hyperplane with the highest margin, or perform any unsupervised clustering scheme, in order to produce the two clusters representing fair vs. unfair projections.

One can also replace the original basis \( B \) with an orthonormal basis for \( \mathbb{C} \) using the Gram-Schmidt process in a general case of a linear subspace spanned by a set of vectors within it. However, in our case, since \( B \) is a linearly independent set, we can achieve the same goal by computing a QR decomposition of a matrix whose columns are our original basis vectors.

A further limitation exists in our use of the USE (Cer et al. 2018). While the USE can be used to embed texts, comparing them is not necessarily one of comparing direct meaning. We tested this by plotting a heatmap of corelations
between the word ‘responsible’, ‘irresponsible’, and ‘not responsible’. Despite the similarity in meaning, the similarity scores found through cosine similarity were different. Whereby the opposite sense of the word ‘responsible’ i.e., ‘irresponsible’ was more dissimilar than the phrase ‘not responsible’ which contained the same word ‘responsible’ (Scores: 0.65 vs 0.89), fig 8 below.

![Fig 8. Heat map of correlation of word using in the vector embedding.](image)

A further limitation is that words used in the sentences, may also carry with them other meanings within the vector space which reflect the vectors use in other contexts such as sarcastically, ironically or even as homonyms (Lee 2021).

Another limitation lies in the problem of pieces of anti-social biased corpora finding their way into the main corpus used for the embeddings. If it were deemed responsible to hurt against someone because of their skin colour, for example, this bias may find its way into the fairness perception metric. In this circumstance, the use responsible in such a singular context would refer to a negative act. To address this, we propose a further metric to be used in conjunction with a fairspace subspace projection. Namely, the use of the Golden Rule (GR), that is, to do onto others as one would have them do unto oneself. Whereby a fair act is one that one would be accepting if it were done onto themselves. Using the logic of the GR, we can assume that no one wishes to be hurt because of their skin colour. Thus, in re-formulating the fairness perception metric to incorporate such a heuristic, it may be possible to avoid such pitfalls. Even if the corpora contain instances of praise for such anti-social acts, reformulating them by asking if the perpetrator would wish this upon themselves offers a possible avenue out of this bias.

Further uses of the technology
In developing the metric further, it may help machines to capture social value dimensions of language, making them more holistic in their interpretation (Zlatev 2001). Practically, it may find itself used across a plethora of domains. For example, legal conflict costs UK organisations £28.5 billion annually, and trillions globally (Acas, 2021). Recent attempts at conflict resolution and arbitration often focus on resolving the problem after it has occurred, instead of prevention (Zerilli et al. 2019; “Contract Dispute Resolution: Surviving Costly Conflict” 2019), and contract analysis software typically focuses on information extraction, redaction, and word processing tools for legal template compliance (Hassan, Le, and Lv 2021). Only a few attempts to mitigate possible conflict by detecting unfair clauses have been made (Lippi et al. 2019; Ruggeri et al. 2021) and none of them have produced an explainable fairness metric. Furthermore, while the focus of this paper has been on textual analysis, it is possible that such a metric can find itself into Artificial General Intelligence (AGI), whereby the AGI converts its visual input into textual representations to process. Much of the literature on AI and ethics revolves around harms and their mitigation (Cervantes et al. 2020). We demonstrate that through a social value vector representation, ethics can also be used positively to assist in the delivery a mechanism to aid socially responsible outcomes and analytics.

Concluding remarks

Some argue that fairness has origins in human nature, with others pointing to social constructivism (Brewer 2004; Corradi-Dell’Acqua et al. 2013). In either case, its representation in language appears to offer a feature that can be used to capture dimensions of a fairness perception. There has been greater implementation of word embeddings as measures in both the scientific domain (Huang and Ling 2019; Ho, Phan, and Ou 2019) and social science domain (Friedman et al. 2019; Kozlowski, Taddy, and Evans 2019). Our paper represents their use in the specialised domain of measuring fairness perceptions. Using representative corpora of human language, it was argued that it is possible to class sentences as being closer to being perceived as fair or unfair, by leveraging an inherent bias. That this bias has its roots in humans being a social species that prefers fair outcomes over unfair ones. A number of further steps must still be taken to produce a fairness metric, such as the digitisation of the golden rule, whereby fair acts are classed as those that an individual would be willing to receive. As well as the implementation of subspace projections for orthonormal representations of the vectors that represent perceptions of fairness.

Code

https://github.com/Anaffinis/Anaffinis/blob/main/Fairness%20Perceptions%20Coding.ipynb
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AI designed the study, coded the software, analysed the results and wrote the manuscript. PR wrote the section on the USE and provided feedback on the paper. SF contributed in critiquing the methods, as well as offering avenues of exploration in the further work section. DS commented on the paper and overall approach used.

Appendix 1

List of 18 fair and 18 unfair sentences selected at random from the longer 200 list. The selection serves for illustrative purposes on vector addition and subtraction outcomes in the paper.

| Fair                                      | Unfair                                      |
|-------------------------------------------|---------------------------------------------|
| The baby smiled at the father             | The man harmed the lady                     |
| The man excused the visitor               | The footballer damaged the goalkeeper       |
| The lecturer amused the students          | The teenager slandered the attendant        |
| The woman picnicked with the man          | The student slurried the teacher            |
| The nurse snuggled the baby               | The killer disfigured the person            |
| Jim hugged Sara                           | The saboteur contaminated the people        |
| The workers savoured the food             | The guard dehumanized the boy               |
| The man serenaded his fiancé              | The spy poisoned the innocent               |
| The groom serenaded the bride             | The father murdered the boy                 |
| The president welcomed the immigrant      | The attendant misinformed the customer      |
| The student appreciated the tutor’s help  | The man demonized the people                |
| The crowd acclaimed the singer            | The woman assaulted the baby                |
| The audience enjoyed the tenor            | The man sickened the lady                   |
| The principal thanked the student         | The organizer mismanaged the crowd          |
| Jack celebrated with Jill                 | Richard brutalized Noah                     |
| The teacher loved the pupils              | The escapee raped the policeman             |
| The nanny comforted the child             | The army slaughtered the children           |
| Tom charmed the woman                     | The teacher crippled the student            |
### Appendix 2

| The baby loved the mother | The suitor paid the saleswoman | The lecturer amused the students |
|---------------------------|-------------------------------|---------------------------------|
| The baby loved the father | The Germans paid the Soviets  | The researcher taught the class  |
| The brother helped the sister | The soldier saved the prisoners | The presenter surprised the audience |
| The boy loved the girl | The lady bathed the baby | The soldier saluted the general |
| The boy cradled the baby | The child obeyed his mother | The painter painted the woman |
| The father loved the baby | The waitress served the party | The child praised a teacher |
| Tom liked Tim | The musician entertained the audience | Jane bullied Paul |
| Jane adored Mary | The student called the professor | Peter killed Joe |
| The girl adored the actor | The man respected the professor | The man killed the man |
| The actor hugged the actress | the man hired the workman | Tom hit Mary |
| The actor kissed the actress | the woman hired the tailor | The wife attacked the husband |
| Mary adored Tim | the manager helped the bullied | Tom cut Mary |
| The girl adored Tom | The husband dined the wife | Paul hurt Bella |
| The man thanked the man | Mary taught Sam | Susan killed Joe |
| The man thanked the woman | The husband hugged the wife | The boy abused the baby |
| The woman thanked the man | The driver found the party | The boy abused his sister |
| The woman thanked the police | The minister loved the congregation | The girl blackmailed the boy |
| The woman thanked the woman | The girl appreciated the suitor | the girl slapped the boy |
| The police thanked the woman | The athlete cheered the crowd | The man scratched the baby |
| The police thanked the police | The man adored his wife | The girl slapped the baby |
| The husband comforted his wife | The driver delivered the passengers | John tortured Tim |
| The groom complemented the bride | The driver comforted the passengers | Sally threatened Louise |
| Mary loved the baby | The actor romanced the actress | The pervert harassed the woman |
| The wife loved the son | The headmaster amazed the pupil | The robber overpowered the resident |
| The man serenaded his fiancé | The headteacher taught the pupils | the pervert harassed the baby |
| Mary appreciated Mike | The president obeyed the senate | The man intimidated the girl |
| The pastor thanked the priest | The worker praised the workmen | The boy harmed the baby |
| The child assisted his father | The worker raised the workmen | The boy mutilated the baby |
| The man charmed the lady | The lady beautified the girlfriend | The boy poisoned the baby |
| The headmistress embraced the girl | The security trusted the manager | The boy dismembered the baby |
| The tailor admired the woman | The manager energized the employee | The boy offended the baby |
| The president greeted the immigrant | The singer excited the audience | The boy killed the baby |
| The man loved his girlfriend | The singer enthused the boy | The boy murdered the baby |
| The police reciprocated the hero | The pilot charmed the stewardess | The boy murdered the baby |
| The woman admired the captain | The teacher loved the pupils | The boy cut the baby |
| The detective welcomed the defendant | The actor heroized the protagonist | The man assaulted the lady |
| The child cleaned the baby | The doctor treated the patient | The man dehumanized the lady |
| The sailor guided the seafarer | The farmer nourished the child | David killed Michael |
| The solicitor advised the client | The farmer fostered the family | The grandfather attacked the grandchild |
| The student tutored the pupil | The caretaker cleaned the house | The general killed his people |
| The Russians helped the Americans | The nurse cleaned the patient | The soldier disfigured his captain |
| Event 1                                                                 | Event 2                                                                 | Event 3                                                                 |
|------------------------------------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|
| The Americans helped the Russians                                      | The scientist taught the attendee                                      | The man murdered his wife                                              |
| The student tutored the friend                                          | The boy hugged the uncle                                                 | The son killed the father                                              |
| The judge freed the prisoner                                           | The crowd cheered the singer                                            | The bride gouged the groom                                             |
| The allies freed the prisoners                                          | The people loved the leader                                              | The baby traumatized Mary                                              |
| The gentleman welcomed the stranger                                    | The nurse treated the patient                                            | The guard tortured the prisoner                                        |
| The man excused the visitor                                            | The surgeon admitted the patient                                        | The female killed the male                                             |
| The colonel executed the child                                          | The corporation polluted the ocean                                       | The horticulturist poisoned the pensioner                               |
| The interrogator burned the suspect                                    | The locksmith robbed the landlord                                       | The guest disfigured the lady                                          |
| The lawyer bribed the judge                                            | The university silenced the professor                                   | James betrayed John                                                    |
| The man destroyed the shop                                             | The university housed the students                                      | The manager extorted the employee                                      |
| The director killed the employee                                       | The professor cheated the students                                      | Jenifer blackmailed the boyfriend                                      |
| The president rejected the refugee                                     | the attacker slashed a stranger                                          | Jenifer assassinated the gardener                                      |
| The lady rejected the man                                               | The man rejected the lady                                                | The party insulted the guest                                           |
| Richard murdered Noah                                                  | the criminal wounded the police                                         | The government terrorized the people                                   |
| Richard terrorized Noah                                                | usher scolded the protestors                                            | The state murdered the prosecutor                                      |
| Richard strangled Noah                                                 | protesters hit the police                                                | The army deposed the winner                                            |
| The criminal tortured the victim                                       | protesters kicked the police                                             | The crowd mobbed the prosecutor                                        |
| The criminal burned the victims                                        | rioters stabbed the police                                               | The crowd killed the protestor                                         |
| The thief stabbed the shopkeeper                                       | The rioters attacked the bystanders                                      | The army executed the innocent                                         |
| The man stabbed the pedestrian                                         | The man killed his friend                                               | Susan abused Kim                                                       |
| Richard brutalized Noah                                                | The clerk murdered his manager                                          | Susan insulted Timothy                                                 |
| Joseph violated Joseph                                                 | The jury convicted the innocent                                          | The child violated the child                                           |
| Patricia assaulted David                                               | Rebecca neglected the baby                                               | The man raped Patrick                                                   |
| The burglar threatened the homeowner                                   | Jonathan tortured the kid                                                | The mother murdered Henry                                              |
| The caretaker poisoned the household                                   | Richard killed Noah                                                     | The gang burnt the lion                                                 |
| The mother decapitated the child                                       | the thief gouged his eyes                                                |                                                                         |
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