Modelling moral choice as a diffusion process dependent on visual fixations

Philip Pärnamets (philip.parnamets@lucs.lu.se)
Lund University Cognitive Science, Lund University, Kungshuset, Lundagård, 222 22, Lund, Sweden
Daniel C. Richardson (dcr@eyethink.org)
Cognitive, Perceptual and Brain Sciences, University College London, Gower Street, London, WC1E 6BT, UK
Christian Balkenius (christian.balkenius@lucs.lu.se)
Lund University Cognitive Science, Lund University, Kungshuset, Lundagård, 222 22, Lund, Sweden

Abstract

A current aim in research on moral cognition is the development of computational models of moral choices and judgements. We fit diffusion models with and without dependence on visual fixations to data on binary moral choices. We find that a fixation dependent model provides a better fit and can capture many features of the empirical data. We discuss the implications for understanding moral cognition and future development of moral choice models.

Keywords: Morality; decision making; eye tracking; computational modelling

Moral Models and Computations

The past decade has seen an explosion of research into moral cognition marked by cross-disciplinary endeavours and findings. While broad theoretical models have been suggested to account for many of the findings in the literature (most notably dual-process models, e.g. Greene et al. 2004) and these models have indeed been fruitful for generating new questions and directions, they are notably lacking in their computational specificity. Providing such specificity is one way of constraining future theorising and providing the ground for mechanistic explanations. Additionally, integration with the rest of cognitive neuroscience might depend on it.

Recently a number of authors have recommended various new directions for developing our current best accounts of moral cognition. One suggestion is to reinterpret findings showing that humans are sensitive to consequentialist or deontological factors when responding to moral dilemmas and instead give an account based on the distinction between model-based and model-free systems from reinforcement learning theory (Crockett, 2013; Cushman, 2013). Another proposal is to move from current stage-based modelling to encompass perspectives where the temporal dynamics of moral processing is given greater importance (Dinh & Lord, 2013). In a similar vein models capturing the dynamics of the controlled and automatic processes competing and mutually influencing one another in the generation of a moral judgement have recently been developed (Van Bavel, Xiao & Cunningham, 2012). Lastly, it has been proposed that physical factors in our environment influence and ground some of our moral intuitions (Iliev, Sachdeva & Medin, 2012). The implication of this work is that part of the moral judgment can be understood as influenced by speed, trajectories and causal features a situation.

What all these examples have in common is that they extend accounts of moral cognition to include domain-general cognitive mechanisms. Here we follow this lead, but consider another direction. We attempt to extend our understanding of what role the visual system might play in determining moral choice by modelling it as a fixation determined diffusion process.

The Attentional Drift-Diffusion Model

Diffusion decision models are originally a class of simple and powerful models originally developed to cover response times for simple binary decisions in perceptual discrimination tasks (see Ratcliff & McKoon, 2008). These models assume that evidence for a response is accumulated stochastically as a function of evidentiary strength until enough has been integrated to pass a decision-threshold. Building on observations that visual fixations play a role in decision processes (Shimojo et al. 2003; Armel, Beaumel & Rangel, 2008), Krajbich and collaborators have proposed an extension of diffusion models to incorporate visual fixations into how evidence accumulation is captured in the model (Krajbich, Armel & Rangel, 2010).

In this model, the attentional drift-diffusion model (aDDM), the drift rate, i.e. the speed at which the decision value is accumulated, is dependent on the direction of the decision makers gaze and proportional to the relative value difference between the fixated and non-fixated alternatives. A formal description is given below. The aDDM has been extended to cover trinary choice as well as simple consumer decisions (e.g. Krajbich et al. 2012), and has been found to be able to predict a number of relationships between gaze and choice.

Present Study

The present study follows from results described in Pärnamets et al. (2013), where we showed that it is possible to influence the content of a moral judgment by monitoring participants' eye-movements as they deliberate between alternatives and prompting their choice at a point in time determined by their gaze behaviour. We found that we could shift participants' choices to a randomly predetermined alternative in 58% of trials.

For this study we let participants respond to the same items as before but without interrupting or interfering with their decisions. We then attempted to fit this data to an aDDM model.

The aDDM model we used is characterised as follows, it calculates a decision value, V_t:

$$V_t = V_{t-1} + d\left(r_{left} - \theta r_{right}\right) + \varepsilon(0,\sigma)_t$$

when the left alternative is fixated, and,

$$V_t = V_{t-1} - d\left(r_{right} - \theta r_{left}\right) + \varepsilon(0,\sigma)_t$$

when the right alternative is fixated. The parameter θ governs the degree of fixation bias in the model; the smaller θ becomes the larger role the direction of gaze matters. The overall drift rate is governed by the d parameter (in units ms^{-1}) while ε_t is white Gaussian noise with variance σ^2. The value updating continues until V_t is equal either +1 (left choice) or -1 (right choice). V_t is assumed to begin at 0.

Methods and Fitting

We first describe the design of the moral choice eye-tracking experiment, and then explain the parameter fitting procedures we used for three models of the data.

Empirical Data

Equipment and Material Eye tracking was performed using an SMI HiSpeed eye tracker recording monocularly at 500Hz. Stimuli were presented on a 19" screen running 1280*1024 pixels resolution using PsychoPhysics Toolbox (Kleiner, Brainard & Pelli, 2007) running on MatLab 2012b (The MathWorks, Natick, MA.). Calibration was performed using a 13 point calibration routine followed by 4 validation points. Calibrations with error exceeding 0.75˚ visual angle in more than one point were rerun. Average error was less than 0.5˚.

As stimulus material we used the set of 63 moral items found in Pärnamets et al. (2013), albeit translated into Swedish. Each items consisted of a recorded proposition, and two alternative answers. An example proposition is "Hurting a defenseless animal is one of the worst things one can do", with the alternatives "It's always bad" and "It's sometimes bad". The alternatives were designed and varied such that it would be informative for participants to view both before giving their answer.

Participants We recorded 18 volunteer participants, recruited through a library noticeboard at Lund University. Average age was 23.7 (SD=0.5) years and 12 of the participants were female.

Procedure Participants were asked to respond to a series of moral proposition by selecting which alternative, of two, they thought was right. Propositions were presented in random order and played to participants through headphones. Throughout the presentation of a proposition participants maintained fixation at a centrally located fixation cross. Once the propositions had been fully played the alternatives appeared, randomly placed right and left on the screen. Participants were given free time to respond and selected their preferred alternative by button press. After each trial they were asked to evaluate how much more right they thought their chosen alternative was in relation to the rejected alternative. The scale contained seven points and was anchored with "Equally right" in one end and "Incomparably better" in the other. This measure is referred to as "goodness difference" throughout.

Once all trials were completed participants were debriefed, asked to sign informed consent, paid and thanked.

θ=1 Model

The first model had θ set to one. This makes value updating independent of fixation directions and the model becomes a regular diffusion decision model. Since fixation direction does not directly affect value integration individual alternative values do not matter directly in the model, only their relative difference. This difference was measured directly in the empirical data. The value update for the θ=1 model is thus the same regardless of fixation direction:

$$V_t = V_{t-1} + d\left(g_{diff}\right) + \varepsilon(0,\sigma)_t$$

In this model there are two parameters to fit, d and σ. g_{diff} was positive if the left alternative was chosen in the original data and negative if the right alternative was chosen.

Fitting First, all the odd trials from the empirical data were selected. Then all first fixations were extracted and saved separately. The remaining fixations from each odd trial were binned according to absolute goodness difference (0-6). For set of parameters and each pairing of item values we ran 1000 simulations. In each simulation we first sampled a first fixation from the distribution of first fixations and then sampled fixations from the distributions fitted to fixations matching the item pairings' absolute goodness difference. Additionally, fixation transition patterns were modelled on the empirical data as a function of the number of fixations already deployed to that alternative.

Second, we computed the log-likelihood of the model for each combination of parameter values as follow. We split the empirical and simulation response times into bins from 0.75s to 12s in 500ms bins. We calculated the probability that a simulation trial occurred in each response time bin and for the empirical data we counted the amount of trials in each time bin. By taking the logarithms of the probabilities in each simulated time bin, multiplying by the corresponding amount of empirical trials and summing them up we arrived at log-likelihoods for each parameter combination where larger (less negative) numbers are better.

We let σ vary as a function of the slope d, letting $\sigma=d*\eta$. We performed first a coarse parameter search and then a second narrow search. In our first search we let $\eta = \{70, 90, 110, 130\}$ and $d = \{0.00001, 0.00005, 0.0001, 0.0002\}$ and in our second $\eta = \{120, 130, 140\}$ and $d = \{0.000075, 0.0001, 0.00015\}$.

Low Value Model

The second model was the aDDM model described earlier where value updating is relative to not only the value difference between items but also to where the participants are currently fixating.

A crucial factor in fitting this model was to convert our measure of goodness difference into separate values for the

alternatives. For each empirical trial we know which alternative was chosen (left or right) and the goodness difference. For this model we simply assigned the non-chosen alternative to always have the lowest possible value (1) and let the chosen alternatives value vary to match that trials goodness difference (1-7). Hence we refer to this model as the "Low Value" model.

Fitting The model was fit using an identical procedure as that described for the θ=1 model except that we also varied the parameter θ. We first searched $\eta = \{70, 90, 110, 130\}$, $\theta = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ and $d = \{0.00005, 0.0001, 0.0002\}$ and followed by $\eta = \{100, 110, 120\}$, $\theta = \{0.4, 0.5, 0.6\}$ and $d = \{0.00075, 0.0001, 0.000125\}$.

High Value Model

The third model was a variation of the second where we changed the assignment of values to the individual alternatives. Instead of holding the lowest value fixed we instead fixed the value of the chosen alternative to the maximum possible value (7) and varied the non-chosen alternatives value (1-7) to match the observed goodness difference. We refer to this model as the "High Value" model.

Fitting The model was fit using an identical procedure for the previous model. We first searched $\eta = \{70, 90, 110, 130\}$, $\theta = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ and $d = \{0.00005, 0.0001, 0.0002\}$ and followed by $\eta = \{60, 70, 80\}$, $\theta = \{0.2, 0.3, 0.4\}$ and $d = \{0.00075, 0.0001, 0.000125\}$.

Analysis

To compare the overall fit of the models we performed likelihood ratio tests using the log-likelihood values from the fitting.

$$LR = 2(LL_1 - LL_2)$$

Where LR is the resulting likelihood ratio statistic (distributed as $\chi^2(1)$) and LL denotes the log-likelihood value of the models being compared.

To assess the fits of the models to various aspects of the empirical data goodness-of-fit statistics were calculated. We used only the even trials from the empirical data throughout. For data where the dependent variable wasn't binary standard χ^2 goodness-of-fit statistics were not possible to calculate. Instead we ran weighted-least-squares (WLS) regressions on the dependent variable corrected by the empirical average, with weights provide by equal to the inverse of the variance of the empirical data at that level of the independent variable. If the model fit the data well the average difference to the empirical data should be zero and we should observe zero coefficients of the WLS regression. We fit the WLS regression as zero intercept and can thus directly compare the (absolute) values of the resulting regression coefficients. The closer a coefficient is to zero the better it fits the empirical data.

Results

Best fitting models

For the θ=1 model the best fitting parameters were found to be $d = 0.000075$ and $\sigma = 0.00975$, with a log-likelihood of *-1905*. The best fitting parameters for the Low Value model were found to be $\theta = 0.5$, $d = 0.0001$ and $\sigma = 0.012$ while for the High Value model the best fitting parameters were $\theta = 0.3$, $d = 0.0001$ and $\sigma = 0.007$. The Low Value model had a log-likelihood of *-1920* and the High Value model *-1884*.

Compared to the θ=1 model, the Low Value model provided worse fit ($p<0.0001$) while the High Value model provided a better fit compared to the θ=1 model ($p<0.0001$). This provides support to the notion that a model incorporating fixation behaviour into the computation of moral choice will provide a better fit than a standard diffusion model. However, the results also show that not any model taking fixations into account will necessarily outperform a basic diffusion decision model.

Basic properties of responses and fixations

Diffusion models all predict that response times should be a decreasing function of evidentiary strength, which with our data means goodness difference. We find that this is the case in the empirical data (**fig 1a**), with a decrease in response times between nearly all levels of goodness difference.

We find that the models capture the general relationship well, with all models to some extent slightly underestimating the empirical response times. Results from the WLS regressions confirm the judgment from visual inspection that the High Value model has the best fit to the empirical data (*β=0.065, SE=0.005*), even capturing the kink in the response time trend caused by the faster responses with zero goodness difference. The θ=1 (*β=-0.161, SE=0.006*) performs marginally better than the Low Value model (*β=-0.179, SE=0.005*).

With decreasing response times as a function of goodness difference we should also observe correspondingly decreasing number of fixations (**fig 1b**). We find, by comparing WLS coefficients, that the High Value model fits the empirical data quite well in this regard (*β=-0.192, SE=0.021*). The θ=1 model fits the data better (*β=-0.521, SE=0.023*) than the Low Value model (*β=-0.592, SE=0.020*) but overestimates the number of fixations while the latter underestimates them.

If we consider fixation durations classified as being first, middle or last, we find in the empirical data similar relationships as have been reported in the literature elsewhere (**fig 1c**). The first fixations are on average shorter than the middle fixations and the last fixations are the shortest. We find that the models consistently underestimate the durations of the middle fixations, likely due to the shapes of the fitted fixation distributions from which the models sample. The last fixations should be the shortest since they should be interrupted whenever the decision barrier is reached. The Low Value and θ=1 model capture

this, while the High Value model produces nearly identical fixation durations for middle and final fixations.

We, last, consider durations of final fixations as a function of goodness (**fig 1d**). We find in the empirical data that final fixation durations are slightly shorter for trials with the highest goodness differences and with no goodness difference, but these differences are not significant (mixed effects regression, 4.86ms per difference step, p=0.07). The θ=1 and Low Value model consistently underestimate the final fixation durations, and we find that the Low Value model produces a better fit (β=-5.53, *SE=0.63*) compared to the θ=1 model (β=-6.18, *SE=0.60*). The High Value model produces the worst fit with especially high durations for the low goodness difference trials (β=-14.57, *SE=1.22*).

The explanation for this can be that when very long fixations (>500ms) are sampled their extended duration are enough to push the model to termination, hence even if they terminate "early" they are longer than average fixations. Empirically such long fixations tend to appear toward the middle of trials something which is not captured by our sampling procedure. This difference becomes more pronounced in the High Value model, since, with low goodness differences being translated into high values to *both alternatives,* the overall drift rate at lower difference levels will be reduced.

Choice and exposure

The empirical data does not show any choice bias a function of first fixation direction (**fig 2a**), with the exception of a surprising trend towards a negative bias with regards to zero difference trials. The Low Value model produces the best fit to the empirical data ($\chi^2(6) = 10.0, p = 0.12$). The θ=1 model fits better ($\chi^2(6) = 10.16, p = 0.12$) that the High Value model ($\chi^2(6) = 16.04, p = 0.01$). The latter introduces weak biases towards the first fixated alternatives in the low difference trials.

Intuitively, any biases towards choosing the first fixated option should derive from longer first fixation durations (**fig 2b**). We see a non-significant trend towards this in the empirical data (logistic regression, p=0.443). The High Value model ($\chi^2(5) = 1.68, p = 0.89$) produces the best fit, followed by the θ=1 model ($\chi^2(5) = 1.69, p = 0.89$) and last the Low Value model ($\chi^2(5) = 1.99, p = 0.85$).

Overall, the last fixated alternative is chosen in 66% of the trials. There is no strong relationship between goodness difference and choosing the last fixated alternative in the empirical data (**fig 2c**), although there is an overall, non-significant, trend of increasing likelihood (logistic regression, β*=0.06, p=0.17*). The θ=1 model, by contrast, predicts no relationship between the last fixation and choice since it does not take fixation direction into account when calculating decision value. Consequently it produces an almost flat 50% line ($\chi^2(6) = 3.57, p = 0.73$). The Low Value model produces the best fit ($\chi^2(6) = 2.87, p = 0.82$) and reproduces the weak, slowly increasing trend found in the empirical data. This can be understood as a function of the consistently low value assigned to one alternative in this model – except in trials with the lowest goodness difference the model will always update (on average) in favour of the high value alternative, albeit at a very slow rate when not fixating that alternative. By, contrast, the High Value model, which exhibits a clear reversed trend, with the last fixation clearly biasing choice in the low goodness difference trials, only exhibits significant updating towards the non-fixated alternative at the highest levels of goodness difference. It is clear that the High Value model fails to capture this portion of the data ($\chi^2(6) = 12.53, p = 0.05$).

We can expect that the longer an alternative has been fixated the more likely it is for it to be chosen. For the empirical data this relationship seems to partially hold (**fig**

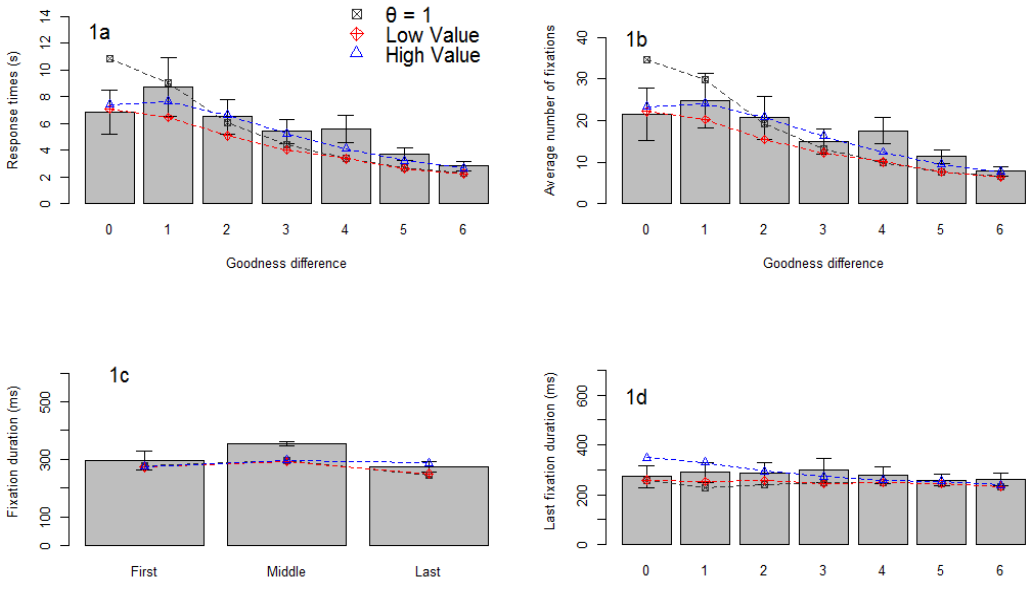

Figure 1. Response times and fixations . **1a**. Average response times as a function of goodness difference. **1b.** Average number of fixations in a trial as a function of goodness difference. **1c.** Average durations of first, middle and last fixations. **1d.** Last fixation duration as a function of goodness difference. Bars denote 95% confidence intervals. Only even trials used for empirical data.

2d). We find that extreme relative time differences have an effect on choice. All three models display increasing likelihood to choose the more viewed alternative as the relative time advantage to that alternative increases. None of the models capture the long inflection in the empirical data. The High Value model produces the best fit ($\chi^2(9) = 39.82, p < 0.0001$) followed by the Low Value model ($\chi^2(8) = 137.36, p < 0.0001$) and last the θ=1 model ($\chi^2(8) = 221.68, p < 0.0001$).

Discussion

We investigated the attentional drift-diffusion model with and without fixations in relation to choices between alternatives in response to moral propositions. We used a post-hoc measure of goodness difference as a measure of evidentiary strength and used this estimate the value of the alternatives to the participants. The results presented here show that moral choices can be modelled as a diffusion process. Most importantly, we demonstrate that including fixations into the model improves the overall fit and that we are able to capture some of the choice related fixation patterns with it.

That taking visual fixations into account should improve a model concerning moral choices might seem counterintuitive at first. Granted there is evidence that visual fixations play a role in decision making in general (i.e. Shimojo et al. 2003, Armel, Beaumel & Rangel, 2008), but those findings are based on choices between faces and foodstuffs, respectively. Both are stimulus-types which, arguably, naturally occur in a visual context. By contrast, in the present study we use fairly abstract propositions. One possibility is that the relationship arises as a function of a general coupling between sensorimotor outputs, eye-movements in particular, and cognitive processing. Such findings are common in other domains, such as linguistic processing (Tanenhaus, Spivey-Knowlton, Eberhardt & Sedivy, 1995), conversational interaction (Richardson, Dale & Tomlinson, 2009) and reasoning (McKinstry, Dale & Spivey, 2008). A general view of cognition that follows is that it is fundamentally embodied; cognition continuously influences and is influenced by sensorimotor processes as a part of its computational setup and moral cognition is in no way exempt from this rule. Here one might object that the causality might be go another way, that participants eye-movements reflect an already formed choice rather than a feedback process. While the models such as the ones presently considered do not constrain the direction of causality other work, in particular that of Pärnamets et al. (2013) has demonstrated that visual fixations not only reflect moral choices but also play a causal role in them.

Another important point to consider is the finding that the Low Value model seems to capture role of last fixations for choice better than the High Value model, despite the latter outperforming its counterpart on almost all other measures. This suggests that participants initially treat their stimulus environment as a High Value one – both alternatives are initially assumed to have high moral value. As the trial evolves and a decision boundary is approached participants transition into being in a Low Value environment, i.e. one where value updating will almost always occur in the direction of the better alternative even if the worse alternative is fixated (albeit at a slower rate). A novel proposal to test in future work would be a hybrid model where alternative values were allowed to fluctuate, while

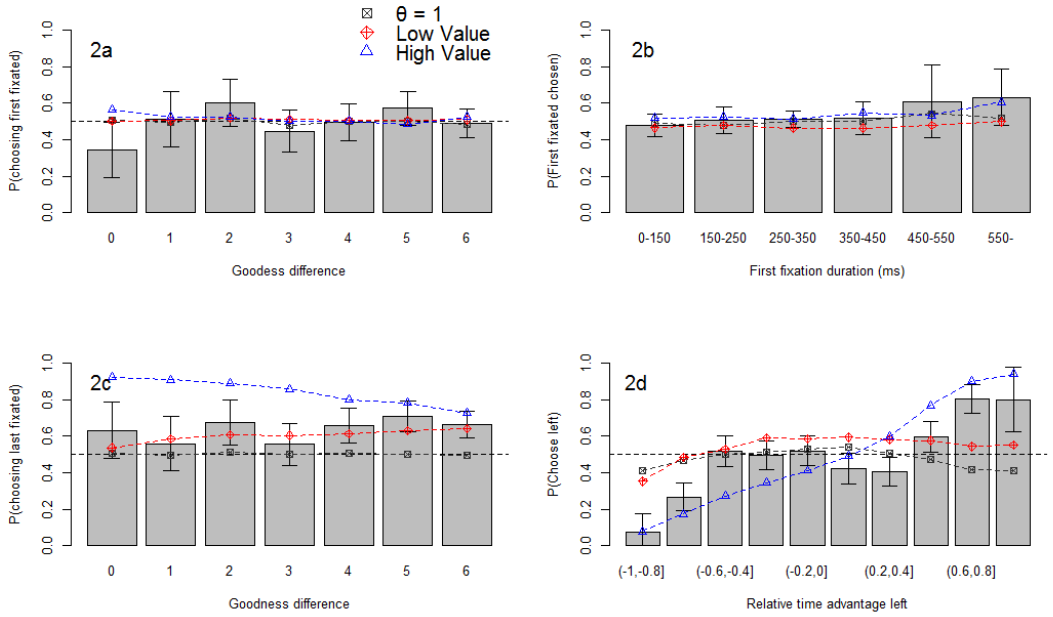

Figure 2. Choice and exposure . **2a**. Probability of choosing the first fixated alternative as function of goodness difference. **2b.** Probability of choosing the first fixated as a function of fixation duration. **2c.** Probability of choosing the last fixated alternative as a function of goodness difference. **2d.** Probability of choosing the left alternative as function of the relative time advantage of that alternative. Relative time advantage is the absolute time advantage divided by total trial time. Bars denote 95% confidence intervals. Only even trials used for empirical data.

keeping their difference constant.

The models evaluated in the current paper have some important drawbacks with regard to their fit to the empirical data which future work needs to address. We note that diffusion decision models were not developed for such long response times as we observe in our task. A remedy is to model the fixation process differently than as a stochastic draw from the fixation distribution at a given goodness difference level. Fixation durations could be made dependent on the amount of time spent in a trial, to capture the effect of longer fixation found in the middle of trials, or as a random variable with an increasing probability to terminate with time. Another possibility is to test models which do away with the assumption of linear integration of evidence found in diffusion models. Indeed, there is some evidence the current fixation direction biases choice processes non-linearly (Pärnamets et al. 2013), but this is yet to be described computationally.

Relatedly, a limitation of the current work is the use of post-hoc comparative valuations. While it has been shown to be possible to recover, at least partially, useful approximations on an alternative-level, the use of goodness difference restricts the modelling in several important ways. First, it removes the possibility of any error. In the present data, participants always choose the highest valued option. This restricts the choice behaviour which can be modelled unnecessarily. Second, having prior valuations would mean that alternatives could be paired against each other to create more variation in the stimulus set. Doing so would entail changing the stimuli as the alternatives in the present study relate specifically to the proposition to which they are attached. A major task for advancing the type of modelling proposed in the current paper within the domain of moral cognition is, thus, to devise a large enough stimuli set of plausible moral statements which can be paired against each other and valued, meaningfully, independently of any extra context prior to choice. Given the evidence presented here and elsewhere for the role of visual fixations in moral and other choices a continued exchange between modelling efforts and experimental evidence appears a fruitful route to progress our computational understanding of moral cognition.

As a final point, we note that the attempting to fit a model which is already successful in other domains addresses not only a call for greater for domain-generality. It can also be used to discover truly domain specific effects as well, as discrepancies between model-fits between domains will stand in need of explanation (see Young & Dungan, 2012 for a similar suggestion). Nevertheless, the present work extends a step in the direction of domain-generality by proposing studying moral choices as choices *simpliciter*.

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