Deciding to Disclose: Pregnancy and Alcohol Misuse

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Abstract

Background

We draw together methodologies from game theory, agent based modelling, and decision theory to explore the process of decision making around disclosure. This is framed in the context of pregnant women disclosing their drinking behaviour to their midwives.

Objective

The primary purpose it to demonstrate the potential utility of an approach which it is hoped goes some way towards addressing concerns about the ad hoc character of ABM[1], by providing a strong theoretical grounding for the reasoning processes of individual agents. To this end we hope to show that these simple rules, operating in an inescapably artificial scenario are nonetheless capable of producing trends from the literature. We also seek to demonstrate the significance of precisely how the decision making process is formulated, by contrasting four distinct decision rules against one another and exploring a simple form of information sharing, supported by the use of statistical emulators for a full exploration of the parameter space.

Methods

We employ game theory to define a signalling game representative of a scenario where pregnant women decide how far to disclose their drinking behaviours to their midwives, and midwives employ the information provided to decide whether a costly referral should be made. This game is then recast as two games taking play against nature, to permit the use of a decision theoretic approach where both classes of agent use simple rules to decide their moves. Four decision rules are explored - a lexicographic heuristic which considers only the link between moves and payoffs, a Bayesian risk minimisation agent that uses the same information, a more complex Bayesian risk minimiser, and a CPT[2] type.

Using a simulator we have developed in Python, we recreate two key qualitative trends described in the Midwifery literature for all the decision models, and investigate the impact of introducing a simple form of information sharing within agent groups. Finally a global sensitivity analysis using GEMs[3] was conducted, to compare the response surfaces of the different decision rules in the game.

Results

Selected results showing the ability of all decision rules to reproduce qualitative trends noted in the literature are provided, together with a sensitivity analysis, and comparitive heat maps produced using GEMs demonstrating the significance of the precise implementation of the decision making.

Conclusions

The ability of all the decision rules to show the qualitative trends suggests that there is some utility associated with this approach.

Comments

We note that the scenario omits the overwhelming complexity of the reality, and is presented largely in the spirit of a convenient demonstration of the methodology. Clearly a domain where there is sufficient data to permit a more comprehensive approach to validation of model outcomes is desirable, and will form the basis of our future work.

[1] Agent Based Modelling
[2] Cumulative Prospect Theory
[3] Gaussian Emulation Machines

To aid in replication and extension, the model has been implemented as a Python module, and is freely available under the Mozilla Public License from `https://github.com/greenape/disclosure-game`, together with full parameter sets, raw data, and all other code used in producing this paper.

1 Introduction

In this paper we extend previous work by Gray (2013).

The case in favour of ABM as a general approach has been made numerously, and elegantly REFS. As such we will not belabour the point, and instead turn to addressing some of the concerns expressed about the method. In this instance we focus on the perception of ABM as ad hoc in nature, tending to be a reflection of the assumptions of the modeller rather than empirically or theoretically grounded (Waldherr and Wijermans 2013). To ameliorate this concern, we draw on decision theory to produce simple rule based, learning, decision making agents and show that they are able to play a form of signalling game with a basic form of intragroup information sharing. Four decision models of varying complexity, and behavioural plausibility are contrasted, by way of demonstrating the significance of the operationalisation of decision making in ABM.

This is framed in the context of disclosure decisions, and a scenario examining drinking patterns in pregnant women which is presented in the spirit of a motivating example, rather than claimed as an accurate representation of reality. Alcohol consumption in the ante natal period is a significant issue in itself, and has been associated with many potentially negative consequences. For example, Andersen et al. (2012) report results from a large scale Danish cohort study suggesting that even low levels of consumption in early pregnancy increase the risk of spontaneous abortion, although Savitz (2012) has suggested this may be attributable to a previously known link to absence of mornining sickness. Risk continues to the point of birth - Kesmodel et al. (2002) found a heightened risk to the infant - into childhood, with a metastudy by Latino-Martel et al. (2010) finding evidence on an increased risk of childhood AML[4] (although they suggest that the rarity of the condition is a limitation). Harm may also extend even further, and a review by Huizink and Mulder (2006) concluded that maternal alcohol consumption could be a contributing factor to ADHD[5], and other learning impairments, but note methodological issues in a number of the papers. There is not, however, a clear consensus, with Gray and Henderson (2006) finding no evidence of harm below 1.5 UK units per day. In terms of official guidance, NICE[6] acknowledge that evidence of harm to the fetus is less than conclusive, but advise not drinking at all, or significant moderation (National Institute for Health and Care Excellence 2010), with similar advice from the Department of Health (2008).

Turning more specifically to disclosure of alcohol use during pregnance, research is relatively sparce, although qualitative trends are reported by Phillips et al. (2007), and Alvik et al. (2006). The former explored factors impacting disclosure through a small case study, highlighting the need to build up rapport over several appointments; the latter compared post partum reports of consumption with contemporaneous accounts, finding apparent underreporting during pregnancy which was amplified by increased drinking. The simulation model described in this paper is able to replicate both qualitative trends, i.e. an increase in disclosure over appointments, and more honest behaviour by moderate as compared to heavier drinkers.

This scenario is of substantial independent interest, and shows the potential utility of a simulation approach in arenas where RCT[7] are not viable for ethical, or financial reasons. With this said, the lack of a strong quantitative evidence base against which to validate the behaviour of the model augers for caution in interpreting the results, and a necessary reminder that in this instance the focus is primarily methodological.

two fold appeal. cognitive plausibility - neuroec. inaccessible systems (litigation, concealment). fast. cheap. portable. theoretical grounding. rigor.

A game theoretic approach to generating an abstract form of the problem gives a convenient, and well known framework to reason about the processes involved in the scenario. While scenarios may well map

[4]acute myeloid leukemia

[5]Attention Defecit Hyperactivity Disorder

[6]National Institute for Health and Care Excellence

[7]randomised control trial

to a plurality of games, this still allows for a principled comparison between interpretations and enforces explicit assumptions. Relating this to decision theory shifts the emphasis away from analytical equilibrium-seeking, and heightens the importance of behaviour change. Where the focus is on the behavioural processes driving a system in motion, and how they change in response to that movement, this is clearly desirable. Fundamentally, the shift of emphasis is from the process of acquiring and inferring the information needed to make choices, to the process of decision. Naturally, this does not preclude the incorporation of strategic refinement, since decision rules are to a great extent modular, and as demonstrated in this paper can be exchanged without altering the underpinning decision problem. In addition, rules are agnostic as to where the information used derives from, suggesting room for multi-stage processes. As a corollary, the decision problem agents attempt to answer can change, allowing agents' behaviour in novel problems to be informed by beliefs derived under other conditions.

A key motivation for decision rules is their claim to provide an account of decision making that is behaviourally and cognitively plausible. Their mooted capability in this regard is to some extent supported by work from neuroeconomics, which aims to empirically test theories of decision making (Rustichini 2009). Many key aspects common to decision rules, for example the idea that a common currency is used by the brain to compare outcomes (Padoa-Schioppa and Assad 2006, 2008), are supported by neurological findings.

Given these features, the application of decision, and game theory to ABM is an attractive approach to computational social science, where the locus of interest is decision making. Taking a balance between the strongly biological, e.g. neural networks, and the more abstract threshold, or microsimulation like models yields a computationally tractable approach. Despite the relative simplicity, it nonetheless captures some of the nuance and sophistication of human decisions.

The remainder of this paper proceeds to provide a brief review of the methodological context (2.1), before outlining the model (3), and experiments (4), with selected results (**??**), then closing with a discussion contrasting the decision models (**??**).

2 Background

This section presents a brief overview of literature focusing on the theoretical underpinning of the modelling approach, with particular reference to statistical decision theory.

2.1 Games, Signals, and Decisions

2.1.1 Signalling Games

Game theory generally deals with strategic decision making in the unusual circumstance of complete information, that is, every player has at least complete knowledge of all possible outcomes, who their opponents are, and so forth. Arguably more generally applicable is the incomplete information scenario, where players lack information about the rules of play in some fashion. Harsanyi (1967) proposed a method for effectively transforming such games into games of complete information by treating the possible variations on the rules as subgames. To determine which subgame is to be played, an additional player - nature - is introduced to make the first move, where nature conducts a lottery according to some probability distribution. If it is assumed that the underlying probability distribution is known to all players, the game is then one of complete information.

Perhaps the best known example of Bayesian games, are the signalling games codified by Kreps and Cho (1987), after initially being framed by Spence (1973) in the context of employment markets. The general form of such a game is that one player holds information known only to them, on the basis of which they send a signal to the other player(s), which the other player(s) then act upon. Much of the interest in signalling games turns on what conditions are necessary for honest signalling to be a Nash equilibrium, or in the context of evolutionary game theory, an ESS[8] .

[8]Evolutionarily Stable Strategy

One approach to this requires that signalling is a costly exercise, as proposed by Grafen (1990) in examining biological signals (for example, the eye-catching but unwieldy peacock tail). Grafen demonstrated that an earlier suggestion by Zahavi (1975), who proposed that such signals were in effect a handicap demonstrating fitness, would lead to an ESS because of the costly nature of the signalling. This solution is also noted by Spence (1973), who showed that a separating equilibrium exists[9] contingent on signals being more costly for some types.

Costly signalling has been applied to explain a variety of apparently contradictory behaviours, for example Godfray (1991) in the context of offspring soliciting food from parents, where the key question is why a behaviour with potentially very high costs (namely, being eaten) would be preferred to a less risky method. In a social context, costly signalling has been proposed as an explanation for religion in human societies. Sosis (2003) developed a model of religious ritual as an exercise in costly signalling, showing that higher costs to engagement in rituals for skeptics maintains the stability of religious groups and the presumed benefits that membership confers. Henrich (2009) extended this idea, and developed an evolutionary model combining cultural transmission with costly signalling in a population, finding that for even modest costs the system moved towards universal belief. Wildman and Sosis (2011) subsequently extended the model, to address the fact that both stable equilibria are binary states, finding that the incorporation of group differentiation allowed subgroups to persist.

Signalling games have also been extended to provide models of other observed human behaviour, for example Austen-Smith and Fryer Jr. (2005) attempted to explain the observed poor academic attainment of some social groups by positing a multiple audience signalling game. They found that the introduction of a secondary signalling game with a peer audience, alongside the prototypical Spence model introduced a pooling equilibrium. Subsequent empirical work by Fryer Jr. and Torelli (2010) has provided some support for this idea. Along similar lines, Feltovich et al. (2002) examine an observed failure by high quality types to signal as would be anticipated, introducing the concept of countersignaling in scenarios where there is noisy leakage of type information. They found that where there is added noisy type information available, separating equilibriums exist where high quality senders signal either as low quality, or not at all.

2.1.2 Bayesian Decision Theory and Expected Utility

Decision theory is the theory of rational decision making (Peterson 2009), this contrasts with game theory which is concerned with strategic decision making. In the broadest sense, the field can be divided into two types of theories: normative, and descriptive. Normative theories are those which attempt to give the rational answer to a decision problem, descriptive or behavioural theories focus instead on characterising the process of human decision making. In this instance, the particular concern is with theories of decision making under uncertainty.

Underpinning almost all theories of decision making, and much of economic theory in general is the concept of expected utility, originally proposed by Bernoulli (1954). This casts decisions as choices between lotteries or gambles, with differing payoffs and probabilities.

Under this model, the expected utility of any gamble is a function of the probability of the outcomes, their utility to the gambler, and the gambler's risk aversion. Essentially this is an extension of the expected value criterion, which assumes that the expected value is based only on the probability and objective value of outcomes. By contrast, the utility framing is a subjective measure, allowing differing preferences between gamblers. Von Neumann and Morgenstern (1953) later formalised the theory, defining rational decision as acting to maximise expected utility, where an individual's preferences are shown to fulfil four axioms, namely completeness, transitivity, independence, and continuity. Completeness requires that for any two lotteries A and B, the decision maker prefers one to the other, or is indifferent. Transitivity requires that if A is preferred to B, and B is preferred to C, then A is also preferred to C. Continuity states that given a scenario as in the transitivity axiom, there is some combination of lotteries A and C where the decision maker is indifferent between that combined lottery and B. Finally, independence maintains that if one were to prefer gamble A to B, that preference holds if both are combined with lottery C.

[9] In fact, an infinite number of them.

While vastly influential, the expected utility theory has been substantially criticised, generally for failing to predict real behaviour. Allais (1953) attacked the independence axiom in particular, suggesting that in some scenarios people's choices would be inconsistent where expected utility implies otherwise. A number of studies (e.g. (Oliver 2003; Burke et al. 1996)) have since supported the intuition to some extent.

More recently, support for some aspects of the expected utility theory, particularly the concept of utility as a common currency for comparison, has come from neurology, for example following work by Platt and Glimcher (1999), Padoa-Schioppa and Assad (2006, 2008) report neuronal firing corresponding to economic value in decision making tasks undertaken by monkeys, while Christopoulos et al. (2009) found similarly indicative results for risk aversion. The suggestion implicit in the model proposed here, that this also applies to social judgements, is less investigated, although both Watson and Platt (2012), and Willis et al. (2010) found that lesions in the brain area[10] identified by Padoa-Schioppa and Assad lead to abnormal social judgements in humans and primates.

Bayesian decision theory, as expounded by Robbins (1964) applies Bayesian inference to the process of decision making under some degree of uncertainty, where decisions may be one-shot, or repeated. The central idea is relatively straightforward, and assumes that the loss or gain of some action to resolve a decision is contingent on an unknown parameter. To solve the problem, the decision maker chooses whichever action will minimise the risk, where the risk of an action is $\sum_i \lambda(a_j|w_i)P(w_i|x)$, i.e. the loss incurred for taking action a_j given that the true state of the world is w_i, multiplied by the belief that this is the true state of world given evidence x, summed across all possible worlds. Essentially this is identical with expected value, with Bayesian style probabilities. This allows an additional process of inference to progressively update the distribution from which $P(w_i|x)$ derives, as new evidence is obtained after each decision.

This approach has been used in a wide variety of scenarios, for example McNamara and Houston (1980) have applied statistical decision theory as a framework for understanding animal learning[11], while Harsanyi (1978) has derived an ethical framework from the principles. Less controversially, in contexts where optimality is desirable as an outcome, Dorazio and Johnson (2003) have used Bayesian decision methods in combination with MCMC[12] to solve complex waterfowl habitat management problems, and Kristensen (1997) has developed robots which utilise Bayesian decision analysis to plan sensor operations.

As with standard expected utility, the Bayesian approach can be criticised, in this case on the grounds of plausibility. The question of plausibility arises from the suggestion that Bayesian inference is in some way a model of human inductive reasoning, as argued by some branches of cognitive science. For example, Tenenbaum et al. argue for the Bayesian approach as a top-down model of inductive reasoning in humans (Tenenbaum et al. 2006; Griffiths et al. 2010), a general approach criticised by Bowers and Davis (2012) as unfalsifiable, overcomplicated, and relying on an unrealistic conceptualisation of the brain as optimal. Miller (2012) also applied similar criticism to claims by Gallistel (2012) that Bayesian inference better characterises learning as opposed to associative conditioning type models, suggesting that this relies on an assumption of optimality which is unfounded.

2.1.3 Descriptive Decision Theory

Arguably the most significant criticism of theories of decision making, is their failure to correspond to empirically observed decision making [13]. This was probably first raised by Simon (1956), who proposed that the apparent divergence derived from a tendency to satisfice, rather than optimise. This suggestion rests on the not unreasonable assumption that people do not have unlimited cognitive capacity (i.e. bounded rationality (Simon 2000)), and hence use heuristic means to make decisions, namely by choosing the first 'good enough' option. Simon suggests that this process nevertheless leads to the optimal solution is most cases.

[10] The orbitofrontal cortex.

[11] Although they note that this is in the sense of how animals 'should' learn, rather than how they do learn

[12] Markov chain monte carlo methods

[13] This critique is not unique to decision theory, and has also been levelled at game theory (e.g. Fehr and Fischbacher (2003) on the irrational altruism of humans playing the prisoners' dilemma).

Subsequent work on descriptive theories largely follows the same framework in assuming that in reality, human decision making is a heuristic process. Tversky and Kahneman (1974) developed three heuristics to explain observed systematic errors in reasoning - representativeness, availability, and anchoring. Representativeness suggests that when asked to judge how related one object or event is to another, they do this based on the extent to which they resemble one another - crucially they will ignore additional, better information when available. Availability claims that when tasked with estimating probabilities, people will rely on the ease with which they can call examples to mind (note that this might be considered an example of satisficing). Finally, anchoring proposes that when estimating, people start with some initial value and progressively update from there, i.e. they will tend to overweight prior evidence at the expense of new information.

Subsequently, Kahneman and Tversky (1984); Tversky and Kahneman (1986) also identified framing effects, which imply that the decisions people make are impacted by the fashion in which the problem is presented. The essential outcome from these findings is that people are risk seeking when faced with outcomes framed as losses, but risk averse towards gains, and regard any loss as greater than an equivalent gain. The impact of framing in itself has been shown to be significant, for example Toll et al. (2007) found improved abstinence rates in smoking cessation where quitting was framed as a gain, and NICE recommend considering the framing of treatment outcomes when presenting options to patients (National Institute for Health and Care Excellence 2007).

PT[14] (Kahneman and Tversky 1979) attempts to provide a decision rule accounting for the heuristic nature of decision making and incorporate framing effects, which successfully explains many perceived failures of rationality. A revised version, CPT (Tversky and Kahneman 1992) addressing a violation of first order stochastic dominance possible under the original formulation, extends the theory to allow decisions with more than two options, but sacrifices the editing phase. Camerer (2004) reviews a number of successes in explaining apparent anomalies with CPT, and argues that should replace expected utility in general usage. Thaler (2000) regards the theory as promising, but points out that it is in many ways incomplete, citing the lack of explanation as to how people construct frames as an example of this.

A significant weakness of CPT as a general theory of decision making is that it fails to account for behaviour under intertemporal choice, or rather does not attempt to address it. Generally, intertemporal choice is assumed to be underpinned by the DU[15] model of Samuelson (1937), which proposes that the value of a thing right now is greater than the value of it at some point in the future (jam today has more utility than jam tomorrow), following an exponential relationship. A more nuanced view of this has been proposed by Ainslie (1991), suggesting that the relationship is hyperbolic rather than exponential. Both models however fail to explain several inconsistencies, for example Thaler (1981) found that discounting rates were different between gains and losses. Loewenstein and Prelec (1992) report a number of additional inconsistencies that are not adequately resolved by DU models, and propose an alternative along the lines of CPT to resolve them while retaining the capabilities of Kahneman and Tversky's model in immediate term choices.

3 Model

In this section we outline the disclosure game model, and give details of the four decision rules, but begin with a brief sketch of a pregnancy in terms of encounters between a woman and a midwife. Typically women will have 12 appointments with a midwife during the antenatal period. Outside of caseloading teams, a woman does not generally have a named midwife, and may see a different practitioner at each appointment. In the UK, and unlike most healthcare scenarios, maternity notes are patient held, so midwives do not have extensive information prior to an appointment unless they have encountered the woman previously. Maternity notes are not generally linked to extra-departmental records, meaning that a history of alcohol related admissions to another service may remain unknown unless revealed by the woman.

According to NICE guidance (National Institute for Health and Care Excellence 2010; National Institute for Health and Clinical Excellence 2010) substance misuse should be raised at the initial booking appoint-

[14]Prospect Theory
[15]Discounted Utility

ment, and subsequent action if a concern is raised is at the discretion of the midwife. This may take the form of specific guidance to reduce intake, or if deemed necessary a referral to a specialist midwife and relevant interdisciplinary team. On alcohol consumption, policy regarding how to determine the level of consumption is generally at the trust level, or according to the best judgement of the individual midwife, with no guidance provided by NICE. This commonly takes the form of average units per week, but may include T-ACE[16] and similar measures.

Beyond the booking appointment, the onus is on women to raise concerns about their drinking behaviour, or the midwife to probe further if they feel it is warranted. In either case, once a concern has been raised the midwife must respond clinically, and inevitably personally, to the information.

In an ideal world, all interactions with healthcare providers would be immediately and fully disclosive, with no repercussions for the patient. However even when considering less emotive topics, this is not the case.

3.1 Disclosure Game

In order to translate the scenario sketched above into a more abstract, tractable form, we cast it as a signalling game, and assume that women's disclosures (or not), are signals. We also make the simplifying assumption that a woman may have one of only three drinking patterns - light, moderate, or heavy. Correspondingly, they are limited in what signals they may send to claiming to be one of these three types.

Midwives are treated in a similar fashion, where their type corresponds to how negatively they regard a drinking pattern - non-judgemental, moderately judgemental, and harshly judgemental. The expression of this judgement is not a matter of choice on their part, and is assumed to have no impact on their response, which is to either refer the woman for specialist treatment, or do nothing.

At the end of a game, each player receives a payoff dependent on the actions and types of both players, which has a partially common interest component. Women receive a payoff based on the health of their eventual baby, with a social cost dependent on the signal they sent and the midwife's reaction to it. Midwives receive the same health payoff as the women, but pay a cost for referring to a specialist, mirroring the organisational cost of non-routine care. Table 1 shows the three payoff matrices which together describe the game.

Taken together, this leads to a game tree that is relatively complex even at the subgame level (figure **??** shows the extensive form for a subgame, with information sets). Rather than attempt to solve for equilibria, agents treat this two player game as taking place against nature, along the lines of adversial risk analysis (Insua et al. 2009). This effectively translates the game to a pair of decision problems, which agents attempt to resolve at each turn using a simple decision rule, given their prior beliefs and experience of play.

Women are drawn in order from a queue, and play against a midwife chosen at random. They play for a maximum of r_w rounds ($r_w = 12$ following the routine number of ante-natal appointments in the UK (National Institute for Health and Care Excellence 2010)) or until they are referred. At which point a new player is drawn from the same distribution that produced the original players to replace them. If they are not referred, they rejoin the back of the queue after their appointment. In either case, they are informed of their payoff after each round and update their beliefs accordingly.

Midwives play for r_m rounds ($r_m = 1000$ in all experiments), and conduct appointments in parallel, i.e. if there are 5 midwives, then five women are drawn from the queue and assigned at random to the midwives. Unlike women, midwives are only informed of their payoff if they choose to make a referral. Both groups of agents have perfect recall, and midwives are assumed to retrospectively update their observations if they make a referral after a number of appointments.

Formally then, let $N = \{m, w\}$ be the set of players each with a private type $\theta_i \in \Theta$, and a set of types $\Theta = \{l, m, h\}$, with pure strategies $A_m = \{r, n\}, A_w = \{l, m, h\}$. Additionally define a utility function $u_i(s_w, s_m, \theta_w, \theta_m) = X_{s,s_w,\theta_m} + X_{h,\theta_w,s_m} + X_{c,\theta_w,s_m}$, and distributions over types $p_w(l, m, h)$, $p_m(l, m, h)$.

[16]Tolerance, Annoyance, Cut down, Eye-opener

		Woman		
Midwife		Heavy	Moderate	Light
	Harsh	0, -2	0, -1	0, 0
	Medium	0, -1	0, 0	0, 0
	Low	0, 0	0, 0	0, 0

(a) Social cost, X_s

		Woman		
Midwife		Heavy	Moderate	Light
	Refer	10, 10	10, 10	10, 10
	Don't refer	-2, -2	-1, -1	10, 10

(b) Health outcome, X_h

		Woman		
Midwife		Heavy	Moderate	Light
	Refer	-9, 0	-9, 0	-9, 0
	Don't refer	0, 0	0, 0	0, 0

(c) Referral cost, X_c

Table 1: Payoff matrices

3.2 Agent Models

While in principle a wide variety of agent models are possible, given that decision rules operate on essentially the same information, and produce the same outputs, we limit ourselves here to four. The simplest is a lexicographic rule (1), motivated as in the spirit of a FFH[17] (Gigerenzer 2004) which uses only information about payoffs given actions; a Bayesian risk minimisation rule using the same information (2); a second Bayesian risk rule (3) which uses information about the underlying lottery; and a two-stage CPT (Hau et al. 2008) agent (4) which is identical with 3, but uses the CPT decision rule from Tversky and Kahneman (1992). Hence, each successive decision model adds a layer of sophistication to the problem representation while retaining the same input-ouput characteristics.

As noted in section 3.1, agents have perfect recall, and recognise individual opponents if they encounter them subsequently. While agents recall perfectly and make use of the new information for retrospective updates, all four agent models make decisions 'as-if' they were always facing a new opponent.

A simplifying assumption is made that all midwives have just qualified after receiving identical training. As a result, they have homogenous beliefs about their women and assume to some extent that they are honest. Women are heterogenous in their prior observations, which are assigned stochastically and constrained such that they have encountered each scenario possible at least once, with exactly k encounters overall.

3.2.1 Lexicographic Heuristic

The lexicographic heuristic (algorithm 1) follows the form of that used in Hau et al. (2008), and assumes a simplified decision problem, as in figure **??**, where an action is a choice between combined lotteries. Functionally, the heuristic maintains a count of the number of times that each action was followed by a payoff, and chooses the action which most commonly has the best payoff, i.e. one reason decision making. This approach requires minimal computation, and does not assume that u_i is static, or known.

Women resolve this by approximating the utility function, as a function $f(s_w, \sigma)$ on their choice of signal and an unknown distribution, which maps to u_w - i.e. s_w is a choice between simple lotteries. The algorithm maintains a count, n, of the number of occurrences of each outcome given the choice from s_w.

[17]Fast and Frugal Heuristic

Midwives solve a slightly different problem with more information, where s_w is known, and s_m is the lottery choice - $f(s_w, s_m, \sigma)$. This is resolved by maintaining a separate count for each signal (i.e. n_{s_w,s_m}), and otherwise following the same algorithm.

Algorithm 1 Lexicographic heuristic

```
n=1, action=none
while action is none do
    Calculate the nth most common outcome following each action.
    Sort actions by the value of the nth most common outcome.
    if clear winner then
        action = best
    end if
    n = n + 1
end while
return action
```

3.2.2 Bayesian Payoff

The Bayesian payoff agent uses the same subset of information as the lexicographic method, but updates beliefs on the link between actions and payoffs using Bayes rule, and attempts to choose the action which minimises risk.

Given the discrete nature of actions and payoffs, coupled with a desire for tractability of the simulation, the Dirichlet distribution is employed to represent these beliefs. The probability density function takes the form -

$$D(\Theta|\alpha) = \frac{\Gamma(\sum_{i=1}^{k} \alpha_i)}{\prod_{i=1}^{k} \Gamma(\alpha_i)} \prod_{i=1}^{k} \Theta_i^{\alpha_{i-1}}$$

Where $\alpha = \{\alpha_1 \dots \alpha_k\}$, k is the number of signal-payoff pairs, $\Theta = \{x_1, \dots, x_{k-1}\}$ all more than zero and summing to less than 1, and α_i is the psuedo-count of prior observations for a pair i.

The distribution is particularly convenient, in that to infer the probability of a signal implying a payoff becomes simply -

$$P(x = j|D, \alpha) = \frac{\alpha_j + n_j}{\sum_j(\alpha_j + n_j)} \tag{1}$$

Where n_j is simply the count of occurrences of pair j, so that the belief that a signal j the number of times that type has been observed (including the pseudo-count), over the total number of observations thus far. This makes computation of beliefs fast and simple, since all that must be maintained is a count of observations with no particular concern as to their order. As before, midwives follow a similar pattern but per signal.

Agents then choose s_i to minimise R_i, which is simply -

$$R_w(s_w) = \sum_{x \in X} -xp(x|s_w) \tag{2}$$

$$R_m(s_w, s_m) = \sum_{x \in X} -xp(x|s_w \wedge s_m) \tag{3}$$

Where X is set of payoffs the agent has observed to follow s.

3.2.3 Bayesian Risk Minimisation

The second Bayesian agent augments the reasoning of the simple payoff model, making the stronger assumption that the utility function is static, and known. Women maintain two sets of beliefs, corresponding respectively to p_m, and the probability of referral given signal choice. This leads to the risk function -

$$R_w(s_w) = \sum_{i \in s_m} \sum_{j \in \theta_m} -u_w(s_w, s_{m,i}, \theta_w, \theta_{m,j}) p(s_{m,i}) p(i|s_w) \tag{4}$$

So that the risk of a signal is the sum of the products of all payoffs with the probabilities of their entailed midwife types and responses.

Midwives reasoning centers on determining the meaning of signals, since given the knowledge of what some signal i conveys about the true type of the sender, the payoff for an action is known. As such, their inference process is the same as for the simple Bayesian agent but over signal-type pairs, and they attempt to minimise -

$$R_m(s_w, s_m) = \sum_{i \in \theta_w} -u_w(s_w, s_m, \theta_{w,i}, \theta_m) p(i|s_w) \tag{5}$$

3.2.4 Descriptive Decision Theory

The most complex decision rule used is CPT, which attempts to reproduce a number of systematic deviations from rationality observed in humans. While CPT has primarily been applied in the context of decisions from description, it has been modified to deal with decisions from experience by incorporating a first stage where probabilities are estimates from observations as in Fox and Tversky (1998). In this instance the Bayesian inference process fills the first stage role.

Rather than the psychologically more interesting PT, the CPT decision rule is used in this instance, because of the requirement for women to evaluate more than two 'prospects'.[18] CPT introduces the concept of a probability weighting function, which underweights small probabilities, and overweights large ones in an effort to capture the tendency of humans to treat high probability events as sure things, and small probabilities as 'never going to happen'. A number of different weighting functions have been proposed, but in this instance the original formulation by Tversky and Kahneman (1992) is used. This distinguishes between weighting for gains, and losses -

$$\begin{aligned} w^+(p) &= \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}} \\ w^-(p) &= \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{\frac{1}{\delta}}} \end{aligned}$$

Where p is the unweighted probability, and γ and δ are the weights for gain and loss probabilities respectively. Humans have also been observed to value gains and losses differently, with a loss being 'worse' than the equivalent gain is 'good'. This entails a transformed value function -

$$v(x) = \begin{cases} f(x) & if\, x > 0 \\ 0 & if\, x = 0 \\ g(x) & if\, x < 0 \end{cases}$$

Where,

[18] A prospect in this instance is a paired outcome and probability, and the set of prospects for an action hence define the outcome space.

$$f(x) = \begin{cases} x^{\alpha} & if\,\alpha > 0 \\ ln(x) & if\,\alpha = 0 \\ 1 - (1+x)^{\alpha} & if\,\alpha < 0 \end{cases}$$

$$g(x) = \begin{cases} -(-x)^{\beta} & if\,\beta > 0 \\ -ln(-x) & if\,\beta = 0 \\ (1-x)^{\beta} - 1 & if\,\beta < 0 \end{cases}$$

And α, and β are respectively the power of a gain, and a loss, and $x = u_i$. The CPT value of outcome x is $v(x)w^{+}(x)$ if $x \geq 0$, and $v(x)w^{-}(x)$ otherwise. For an action the CPT value is the sum of the value of the prospects of that action, as in the Bayesian risk model. The decision rule then requires the agent to choose the action which maximises the prospect theory value.

3.3 Information Sharing

It would seem unreasonable to suppose that neither party recounts their experiences to their peers, and to explore the impact of this we also modify the game to introduce a simple form of information sharing within agent groups. This takes the form of having each agent share their memories with their colleagues with some probability q. Individuals then incorporate shared information into their beliefs using weighted updates, such that a shared observation of a low type signal contributes to their beliefs by w, and $0 \leq w \leq 1$ (i.e. $n_j = n_j + w$). Women share only when they have finished play, and provide their complete history of games, because they have accurate information about the outcomes. By the same rationale, midwives share only their history with the most recent woman they referred. Sharing occurs simultaneously for all players at the end of each round, and all memories are either shared immediately or discarded.[19]

Because of their differing problem representations, the simple payoff reasoners and their more complex counterparts incorporate this exogenous information differently. The simple payoff based rule relys on a belief structure relating actions directly to rewards. Because payoffs differ by the agent's private type, the information shared may not correspond to the experience of the listening agent in the same scenario. As a result, payoff reasoners have a belief bias towards the most common player type, and can believe in outcomes that are, for them, impossible.

By contrast, representing the problem in terms of the probabilities of the individual lotteries yields a structure that abstracts the new information from payoffs, and allows the agent discount implausible outcomes. This stronger assumption as to the static and known qualities of payoffs does however reduce the flexibility of the decision rule.

4 Method

This section provides details of experiments conducted to examine the ability of the model to reproduce qualitative trends reported in the midwifery literature by Alvik et al. (2006), and Phillips et al. (2007); as well as a global sensitivity analysis and construction of statistical emulators to explore, and contrast the response surfaces of the four decision rules.

4.1 Qualitative Trends

Throughout this paper, parameters for the CPT model were as used in Tversky and Kahneman (1992) (table 2). While there has been significant work on determining appropriate parameterisation for the model (e.g. Neilson and Stowe (2002), Glöckner and Pachur (2012), Nilsson et al. (2011)), a full exploration of the impact of these parameters, or heterogeneous values within populations is beyond the scope of this work.

[19] Memories of games remain, but it is assumed that only current news is relevant.

Name	Description	Value
n_w	Number of women	1000
n_m	Number of midwives	100
r_m	Number of appointments per midwive	1000
r_w	Maximum number of appointments per woman	12
Runs	Simulation runs	1000
$p_w(h)$	Proportion of heavy drinkers	1/3
$p_w(m)$	Proportion of moderate drinkers	1/3
$p_w(l)$	Proportion of light drinkers	1/3
$p_m(h)$	Proportion of harsh midwives	5/100
$p_m(m)$	Proportion of moderate midwives	10/100
$p_m(l)$	Proportion of non-judgemental midwives	85/100
q_w	Probability of women sharing	0.
w_w	Weight of shared information for women	0.
q_m	Probability of midwives sharing	0.
w_m	Weight of shared information for midwives	0.
$s_i[a_i] : s_i[a_{\neg i}]$	Psuedo-count favouring honesty	10:1

Table 2: Model parameters.

Two key measures were used - the fraction of the subpopulation who had ever signalled honestly, and the proportion referred. Both measures were taken after every round of play, and were taken relative to the agent's position in their sequence of appointments giving the probability of signalling honestly, or being referred having had a given number of appointments.

4.2 Global Sensitivity Analysis

In general, we follow the procedure outlined in Bijak et al. (2013) for stochastic

Parameters for training were generated in R (R Core Team 2014) using Latin Hypercube Sampling (Carnell 2012) over the space of inputs given in table **??**, giving 10 free parameters. Initially a unit hypercube was generated, then the margins transformed appropriately to cover those regions where the inputs are not bounded between 0 and 1, and for proportions of agent types which necessarily sum to one across the three parameters. Given the limitation of 400 design points for the GEM-SA[20] software, we produced exactly that many parameter combinations and collected results for 100 runs of each. A fixed set of 100 random seeds was used, such that each parameter set was run once with each seed, for every decision rule.

To better capture the response characteristics for the model, we measure three outcome variables - (1) the interquartile range of the average signal sent by each type of agent in a run, (2) the average signal of moderate drinking agents in a run, and (3) the standard deviation of that average signal between simulation runs. Together these three metrics give an indication of how far women are separable by their signalling behaviour (1), the behaviour of the at risk drinking groups[21] (2), and finally the stability of the system in the face of the stochastic elements.

Measurements were taken at the end of 1000 rounds of play, and for 1 and 2, 400 results were selected covering the full hypercube with each chosen randomly from the runs for that design point. This approach, rather than averaging across runs, was taken to avoid obscuring the high degree of variability evident in the output of the payoff reasoning agents in some areas of the parameter space.

Twelve emulators were built, covering each of the three output on all four decision models. These emulators were used to conduct a probabalistic sensitivity analysis using GEM-SA to assess the impact of parameters individually, and in combination.

[20]Gaussian Emulation Machine for Sensitivity Analysis

[21]Under most conditions, the behaviour of heavy drinkers tracks closely with their moderate counterparts.

Name	Description	Min	Max
$p_w(h)$	Proportion of heavy drinkers	0	1
$p_w(m)$	Proportion of moderate drinkers	0	1
$p_w(l)$	Proportion of light drinkers	0	1
$p_m(h)$	Proportion of harsh midwives	0	1
$p_m(m)$	Proportion of moderate midwives	0	1
$p_m(l)$	Proportion of non-judgemental midwives	0	1
q_w	Probability of women sharing	0	1
w_w	Weight of shared information for women	0	1
q_m	Probability of midwives sharing	0	1
w_m	Weight of shared information for midwives	0	1
$X_{h,}$	Health payoff for healthy delivery	1	100
$X_{c,r}$	Cost for referral	$-(X_h - 1)$	
$s_i[a_i] : s_i[a_{\neg i}]$	Psuedo-count favouring honesty	1:1	100:1

Table 3: Parameter ranges.

Name	Description

Table 4: Output measures.

5 Results

LOOK AT MAH GRAFS!

5.1 Qualitative Trends

All four decision rules were able to reproduce both qualitative trends, and are in that sense comparable.

Figure 1: Average fraction of population signalling honestly over appointments, across 100 runs.

5.2 Sensitivity Analysis

6 Discussion and Conclusions

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