Introduction

Human risk-propensity is believed to be inherently risk-aversive (Dan & Loewenstein, 2020; O’Donoghue & Somerville, 2018). However, this belief originates from prospect theory in which risk-taking behaviour can be thought of in terms of how the prospect of uncertainty in a decision is believed to materialize itself for the individual making a choice, i.e., whether the decision yields possible gains or losses (Tversky & Kahneman, 1979, 1989). Prospect theory is traditionally applied to econometric contexts but has been shown to be widely applicable to a whole range of other domains such as choice-behaviour in travelling (van de Kaa, 2010), expected utility represented by expected years of living as a function of health-choices (Attema et al., 2013), and in explaining political science models (McDermott, 2004).

The study at hand builds on prospect-theory ideas that risk-propensity follows a non-linear function and that negative losses are weighted heavier psychologically than positive gains in choice-settings (Weller et al., 2011). Namely, ideas that loss-aversion is an in-built anthropological defence-mechanism that allows individuals to survive and pass on their genes. In a paper on the evolutionary mechanisms introduced by stochasticity across generations Zhang et al. (2014) claim that risk-aversive behaviour has inherent evolutionary benefits across generations and species. Furthermore, they use a simple binary-choice model to highlight individual differences in choice-behaviour and link the variability to stochastic patterns of natural selection. This paper is particularly concerned with the individual variance of risk-willing behaviour in a natural backcountry skiing context in which a binary choice yields the highest possible loss, i.e., death, and merely poses recreational fun as the potential gain.

Multiple studies have demonstrated that humans differ in their decision-making outcomes when deciding whether to ski certain areas of a mountain when ski touring. One study approached avalanche prediction from a pure-bayesian approach in which probabilities of triggering an avalanche was calculated with an adaptation of Bayes’ theorem (Ebert, 2019). In this study it is highlighted that people vary in their decisions regardless of the avalanche-risk presented to them. Furthermore, the paper argues that irrespective of the fact that Bayesian reasoning is a great tool for predicting the probability of triggering an avalanche, the introduction of it in avalanche-education curricula should be done with extreme caution. This is because Bayes’ theorem is unintuitive in its nature and that people have demonstrated an inability in using it correctly (Westbury, 2010). A study on people’s integration of heuristic information concluded that people are often predetermined to ski somewhere regardless of information from the environment that would make it more reasonable not to (Michaelsen & Rolland, 2016). Furthermore, habits more so than any other reason predicted whether people were going to ski. Thus, people are inclined to have certain routes that they ski depending on the weather that they would decide on prior to entering the mountain, as opposed to incorporating dynamic information from the environment, they are skiing in and basing their decision on that. Other papers have shown the importance, however, of utilizing different predictive elements to achieve skiing without causing avalanches. A two-part paper by McClung (2002a, 2002b) has attempted to incorporate both physical and human issues in avalanche forecasting. He argues that avalanche prevention presents itself as a dynamic problem constituted of both geotechnical predictors and human elements. He goes on to say that most avalanches are caused by human triggers. He divides avalanche prediction into seven subcomponents: definition, goal, human factors & perception, reasoning process, information types & informational entropy, scales in space & time, and decision making. The paper at hand attempts to build on these findings but is primarily concerned with the human variability on self-informed decisions in a skiing context i.e., the seventh element from McClung’s proposed framework. Other elements will be entertained in the discussion.

Over the cause of a season two skiers are tasked with risk-assessment of skiable terrain and to report whether they opted to ski the terrain. The risk-assessment followed a pre-made avalanche evaluation system. Cognitive modelling was done to capture proposed Bayesian mechanisms in risk-assessment and risk-propensity.

Methods

* 1. Participants

Two individuals participated in this proof-of-concept study. Both were males and were 23 and 24 years of age respectively. Both participants were expert skiers and ski-touring experts. Written informed consent was obtained before participation to comply with the Declaration of Helsinki. The participants reported 13 and 25 skiing assessments in 3 different countries between the 28th of February 2023 and the 6th of May 2023.

* 1. Experimental Design

The study was conducted using The Avaluator™ Version 2 slope evaluation card developed by Avalanche Canada (*The Avaluator*, 23/05/2023). Participants were asked to assess various avalanche conditions and terrain characteristics to get a two-dimensional score that would place their decision to ski/not to ski within a two-dimensional risk-evaluation space. Both the avalanche conditions and the terrain characteristics were comprised of sub-categories the participants were asked to report as binary scores (0 if the phenomenon was non-present, 1 if it was present). The sub-categories and their description can be seen in table 1 similarly to how they were presented to the participants.

|  |  |  |  |
| --- | --- | --- | --- |
| **Avalanche Conditions** | **Score if phenomenon is present** | **Terrain Characteristics** | **Score if phenomenon is present** |
| **Regional Danger Rating**: Is the avalanche danger rating “Considerable” or higher | +1 | **Slope Steepness**: Is the slope steeper than 30 degrees? | +1 |
| **Persistent Avalanche Problem**: Is there a persistent or deep persistent slab problem in the snowpack | +1 | **Terrain Traps**: Are there gullies, trees, or cliffs that increase the consequences of being caught in an avalanche? | +1 |
| **Slab Avalanches**: Are there signs of slab avalanches in the area from today or yesterday? | +1 | **Slope shape**: is the slope convex or unsupported. | +1 |
| **Signs of instability**: Are there signs of snowpack instability including *whumps*,shooting cracks, or drum-like sounds? | +1 | Forest Density: Is the slope in the alpine, in a sparsely treed area or in open forest (cut-block, burn, wide-spaced glades)? | +1 |
| **Recent Loading:** Has there been loading within the past 48 hours including roughly 30 cm of new snow or more, significant wind transport or rain? | +1 |  |  |
| **Critical Warming:** Has there been a recent rapid rise in temperature to near 0 C, or is the upper snowpack wet due to strong sun, above-freezing air temperatures or rain? | +1 |  |  |
| **Avalanche Conditions Score** | Accumulation of all avalanche conditions scores. | **Terrain Characteristics Score** | Accumulation of all terrain characteristics scores. |

Table 1, shows the Avaluator Slope Evaluation card. Avalanche conditions score for a given run ranges from 0-6, and terrain charcteristics score ranges from 0-4. Note that for the version of the Avaluator provided by Avalanche Canada the characteristic “Slope steepness” can get a score of +2 if the terrain is steeper than 35 degrees. For experimental reasons this characteristic was simplified.

As seen from table 1, the avalanche conditions score for a given run was an integer between 0 and 6, and the terrain characteristics was an integer between 0 and 4. The Avaluator System gives a dynamical hint of the riskiness of a decision by placing the overall evaluation of the given run within a two-dimensional space where a decision to ski a run can be accompanied by “Caution”, “Extra Caution”, or “Not Recommended”. See figure 1 for an illustration provided by Avalanche Canada.

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Figure 1, shows the two-dimensional space the assesment scores from table 1 can range within. Terrain characteristics are shown on the horisontal axis and range from 0-4 as indicated by the dashed, white lines. Avalanche conditions are shown on the vertical axis and range from 0-6 as indicated by the dashed, white lines. The avaluator system recommends the level of caution a skier should have when skiing in different combinations of terrain characteristic scores and avalanche conditions.

As seen from figure 1, the slope evaluation does not give the skier a definitive answer as to whether a run is safe to ski or not. It serves as an assistive tool in the decision making process of choosing to ski/choosing not to ski. The partcipants were asked to report whether they chose to ski or whether they chose not to ski along with their avalanche conditions and terrain characteristic assessments.

1.3 justification of methodological approach

In its core, the aim of this paper was to infer strategies or underlying driving mechanisms from decision-making behaviour in a skiing context. The obstacles tackled by the researcher to illuminate these mechanisms consequently presented themselves as specific cases of ‘the inverse problem’ in which what the researcher has at their disposal is overt observations, and what the researcher is interested in is the underlying hidden causes that drive the behaviour responsible for those overt observations. Different cases of Bayesian Cognitive models were implemented on the avalanche decision making data to estimate parameters that are fitting with the observed choices from the empirical data.

1.4 simple Bayes Model

A hierarchical simple bayes model was implemented to allow for multiple sources of information to impact the outcome of skiing or not skiing *O* on a given run *r* for a given skier *s*. The simple bayes model was implemented as:

In which *β* is a parameter called *bias* to be estimated by the model, *a* is a source of information obtained by the skier, namely the avalanche conditions observed on a given run, and *t* is another source of information obtained by the skier, namely the terrain conditions for a given run. The model thus attempts to estimate a *β*-parameter from two different sources of information and the given outcomes for the combination of different values of those sources of information.

1.5 Weighted Bayes Model

An adaptation of a simple bayesian model with weights for the sources of information was also implemented (Jardri et al., 2017). The weighted bayes model followed the same logic as the simple bayes model, with the important difference that it allowed for the two sources of information to be weighted relative to one another, i.e., two additional parameters were introduced for the model to estimate. was the weight parameter for the first source of information *avalanche conditions (a)*, while was the weight parameter for the second source of information *terrain characteristics (t)*. The whole model was therefore given by:

1.6 simulating data

It is common practice to validate a statistical model by simulating data from the proposed experimental setup before collecting data. By doing so, the researcher is allowed to test the model on data that is completely known to them and thereby check if the model produces results that should be expected from the scientific reasoning gone into the formulation of the model. 10 agents were simulated to each ski 100 runs. The data was passed to the model, and this made it possible to see if the bias parameter could be successfully recovered for both realistic values, but also for more extreme cases. The data was simulated to most accurately mimic the decisions made by the skiers in the empirical data who used The Avaluator System. Detailed information about the data simulation can be found in the GitHub repository linked at the start of this paper.

1.7 Model Quality Checks Simple Bayes

Prior posterior update checks were done on the simulated data to assess how well the model learned from the simulated data. It is seen from figure x that the model learns from the data and that the model consistently overestimates bias. This is something to be wary about when fitting the model to empirical data.

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Figure 2, visualizes prior densities for the siimulated skiers with the pink curve. The blue distribution shows the posteriors estimated by the model. The black, dashed line illustrates the naïve, simulated mean bias.

Visualisations of the two Markov chains show great mixing of the two chains for bias in the simplebayes model. The visualisations show that the model converges appropriately.

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When choosing a prior for the bias-parameter in the model different priors where used in prior predictive checks of the outcome. Thus, 4 meaningful priors for bias were used to assess the influence of prior values on the accumulated outcome of skiing/refraining from skiing. The results can be seen on figure x.

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As seen from figure x the influence of the prior for bias is quite influential on how the model predicted the accumulated outcomes of 6000 simulated skied runs. The \*0.7-adjusted prior yielded predictive outcomes most compatible with the hypothesized number of total skied runs and this prior was therefore chosen for the final model.

A prior sensitivity analysis was also made to assess how priors affected the posterior distribution of the bias-parameter. As seen from figure x, the prior influenced the posterior distributions as would be expected, i.e., smaller values of standard deviations for the prior distribution resulted in the prior having a larger effect on the posterior distribution.

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1.8 Model Quality Checks Weighted Bayes

Prior posterior update checks were done on the simulated data to assess how well the model learned from the simulated data. It is seen from figure x that the model learns from the data and that the model consistently overestimates bias compared to the simulated mean bias. This is something to be wary about when fitting the model to empirical data as any bias value would potentially also be overestimated for the empirical data.

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To test if the two models produced results that captured parameter values for both realistic and rare cases, parameter recovery was done. In effect, the proposed parameter values from the simulated skiers were compared to the estimated values from the model outputs. All parameters were recovered successfully and thereby confirmed the mathematical reasoning that had gone into simulating the data and into the models themselves. Figure x shows the parameter recovery for the parameters in the weighted bayes model. See appendix for parameter recovery for the bias parameter from the simple bayes model.

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Results

1.1 Simple Bayes Model

Both participants displayed a bias for skiing with 95% credible intervals within well above 0.5 (see table x for full summary output). There was, however, a noticeable difference in their posterior bias distributions. Subject A had a posterior distribution with a mean that was considerably higher than the hypothesized naïve true mean, i.e., 0.5 versus 0.75, while subject B had a mean that was even higher, i.e., 0.83. This suggests that there is a difference in the decision-making process of choosing to ski or not irrespective of consciously thought-out assessments of the risk involved in choosing to ski. Subject A is more risk-aversive than subject B that has a higher bias towards choosing to ski.

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Figure 3, shows densities for the priors and posteriors for the bias parameter in the simple bayes model. The pink distributions are normally distributed around 0.5 and display the prior distributions. The blue distributions illustrate the posterior distributions for the estimated posteriors for the bias parameter for the two subjects. The dashed line shows the naive hypothesized bias of 0.5.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Mean | Median | Standard Deviation | MAD | q5 | q95 | rhat | ess\_bulk | ess\_tail |
| Bias Posterior  Subject A | 0.73 | 0.74 | 0.08 | 0.08 | 0.59 | 0.85 | 1.0001 | 6355 | 4325 |
| Bias Posterior  Subject B | 0.83 | 0.84 | 0.09 | 0.08 | 0.66 | 0.95 | 1.0004 | 6102 | 4603 |

Table 2, shows summary output for the two subjects for the bias-parameter.

* 1. Weighted Bayes Model

The differences in the bias parameter values between the two subjects became considerably less obvious for the weighted bayes model compared to the simple bayes model. The mean -value for subject A was 0.7, while it was 0.73 for subject B. Both subjects, however, displayed a far greater bias towards skiing than the hypothesized naive mean of 0.5. Subject A had a mean -value of 0.59, while it was 0.6 for subject B. The -parameter was also quite alike for the two subjects with mean-values of 0.58 and 0.56 respectively.

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Figure 4, shows densities for the priors and posteriors for the bias, weight1, and weight2 parameters in the simple bayes model. The pink distributions are normally distributed around 0.5 and display the prior distributions. The blue distributions illustrate the posterior distributions for the estimated posteriors for the bias parameter for the two subjects. The black, dashed lines show the naive hypothesized parameter values. The grey, dashed lines show the 95% credible intervals for the parameter values.

Looking at figure x, it looks like the two subjects had similar parameter distributions. However, the pattern of subject B being more biased towards skiing that was seen in the simple bayes model is still somewhat visible in the weighted bayes model. The tails of the posterior distribution seems somewhat longer for subject B, indicating more fluctuation for this subjects bias value between decisions. The

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Mean | Median | Standard Deviation | MAD | q5 | q95 | rhat | ess\_bulk | ess\_tail |
| Bias Posterior  Subject A | 0.7 | 0.71 | 0.07 | 0.07 | 0.57 | 0.82 | 1.001 | 6749 | 5257 |
| Bias Posterior  Subject B | 0.73 | 0.74 | 0.1 | 0.1 | 0.55 | 0.88 | 1.001 | 6621 | 5496 |
| Weight1 Posterior  Subject A | 0.59 | 0.59 | 0.04 | 0.04 | 0.54 | 0.66 | 1.0005 | 4421 | 2473 |
| Weight 1 Posterior  Subject B | 0.6 | 0.6 | 0.04 | 0.04 | 0.54 | 0.67 | 1.002 | 5084 | 2307 |
| Weight2 Posterior  Subject A | 0.58 | 0.58 | 0.03 | 0.04 | 0.53 | 0.64 | 1.0008 | 4649 | 2395 |
| Weight2 Posterior  Subject B | 0.56 | 0.56 | 0.03 | 0.03 | 0.53 | 0.62 | 1.0002 | 3659 | 2335 |

The models were compared using leave-one-out cross-validation for the model fits. Looking at the values in table x, it became clear that the weighted bayes model best fit the data. This is because the leave-one-out information criteria was lower for the weighted bayes model i.e., 27158.5 compared to 27674.3 for the simple bayes model. However, looking at how much the

|  |  |  |
| --- | --- | --- |
|  | Simple Bayes (SE) | Weighted Bayes (SE) |
| ELPD Loo | -13837.2 (56.3) | -13579.2 (75.2) |
| P Loo | 3.0 (0) | 23.3 (0.3) |
| LOOIC | 27674.3 (112.6) | 27158.5 (150.5) |

Table 3, shows model fit estimates for the two models. The estimates are computed using leave-one-out cross-validation. The standard error for the estimates are written in parentheses.

Discussion

The paper found a difference in the decision-making process for the two subjects. In fact, the difference was noticeable and could be convincingly reduced to differences in risk-aversion. This is because the decision was made consciously explicit to the subjects themselves, as they were the ones gathering the information, they were basing their decision on. The subjects were asked to consciously consider the levels of danger associated with choosing to ski by using a system created to remove the decision from individual assessments. Despite this there was a clear difference between the subjects’ prevalence for opting to ski or not to ski. This difference in decision-making might be partly explained by personality, as personality traits have been extensively linked with risk-propensity across domains (Mishra & Lalumière, 2011; J. Zhang et al., 2020). Traits such as competitiveness and preference for a fast-paced life, low levels of anxiety, lack of straightforwardness, lack of self-discipline, and spontaneity have been found to have a positive relationship with risk-propensity (Nicholson et al., 2005).

Appendix

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