The Value of Uncertainty: A Reinforcement Learning Model of Increased Risk Seeking During Gambling With Near-Miss Outcomes

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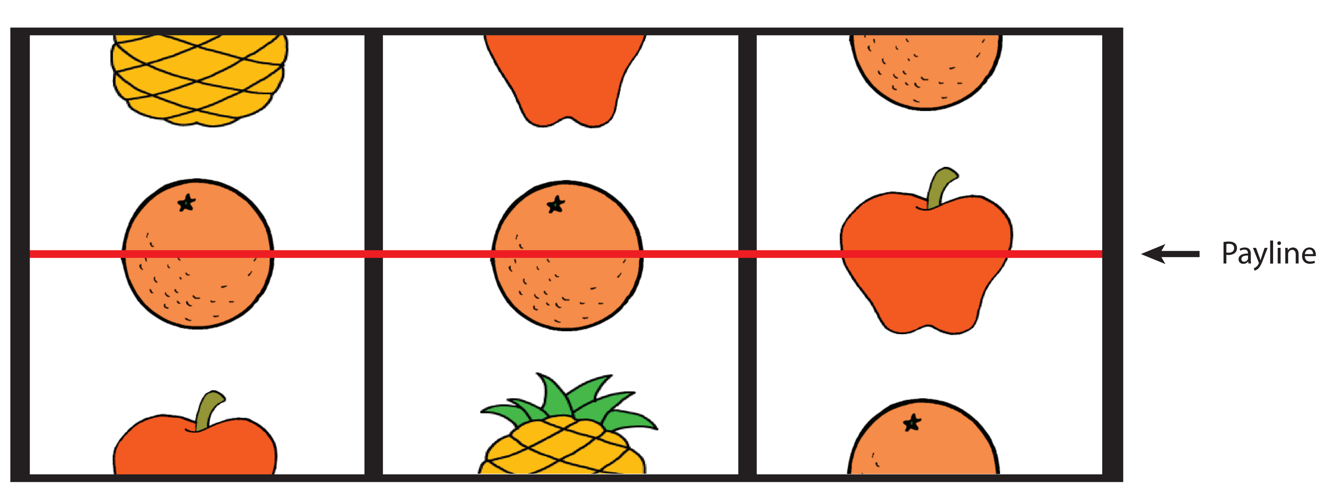
Introduction

The near miss is thought to influence the way players interact with Electronic Gambling Machines (EGMs)[1]. Thus, many gaming manufacturers have designed their machines to produce near misses at levels greater than chance in order to increase entertainment value.

In a natural environment, predictions about the riskiness of a behaviour are vital for guiding future action. The accuracy of these predictions maintain varying degrees of certainty based on previous outcomes. When uncertainty is high, individual outcomes have a greater influence on future behaviour. EGMs that include a high occurrence of near misses may be manipulating the normal role of uncertainty by increasing the perception that inherently uninformative feedback is a useful predictor of future reward.

In this study we artificially increased the proportion of near misses in a gambling task. We then modelled the observed behaviour using several computational reinforcement learning[2] models.



Methods

Computational models were developed and analyzed using Matlab (the Mathworks, Natick, MA).

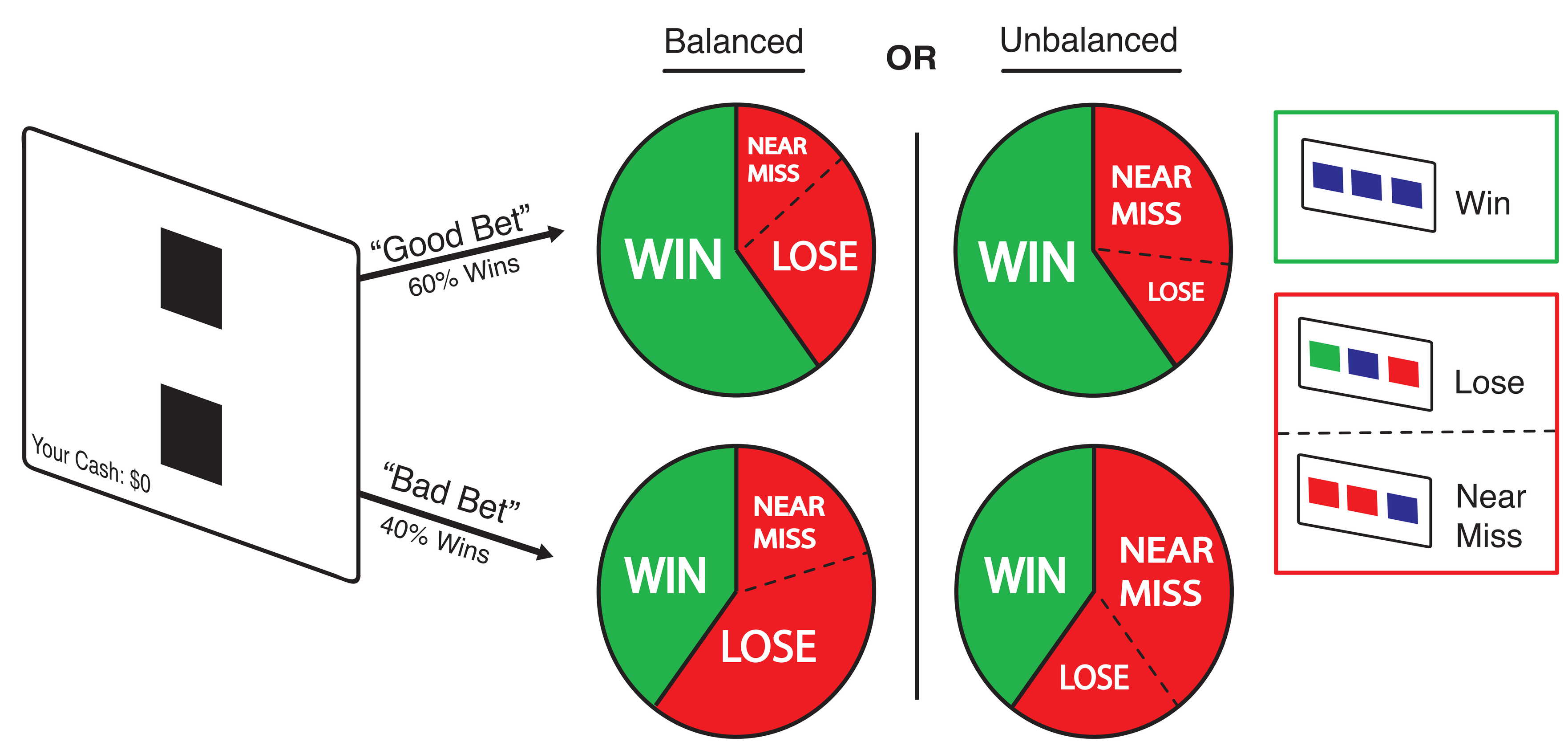
Goodness of fit was calculated using the maximum Log Likelihood Estimation (LLE) method.

The parameters that produced the maximum LLE were found using an interior point algorithm.

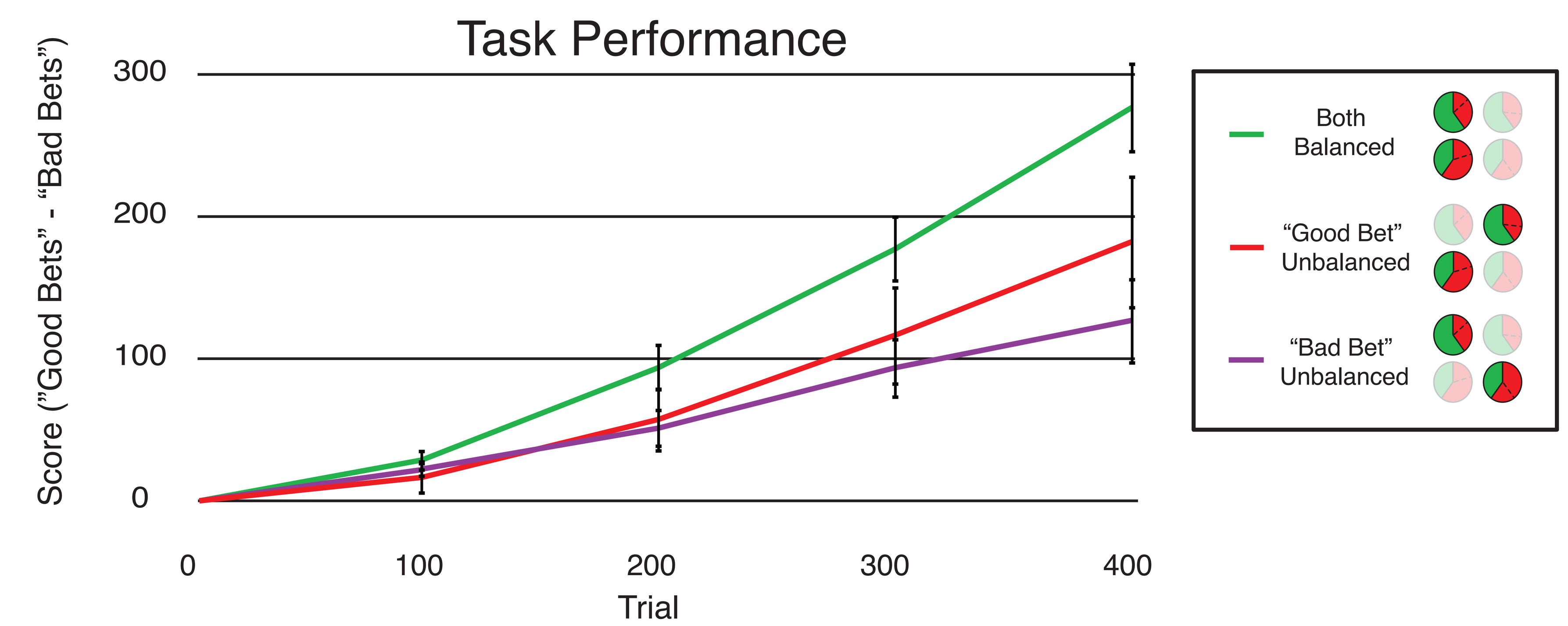
Recorded with dense-array EEG (128 Channel EGI system).

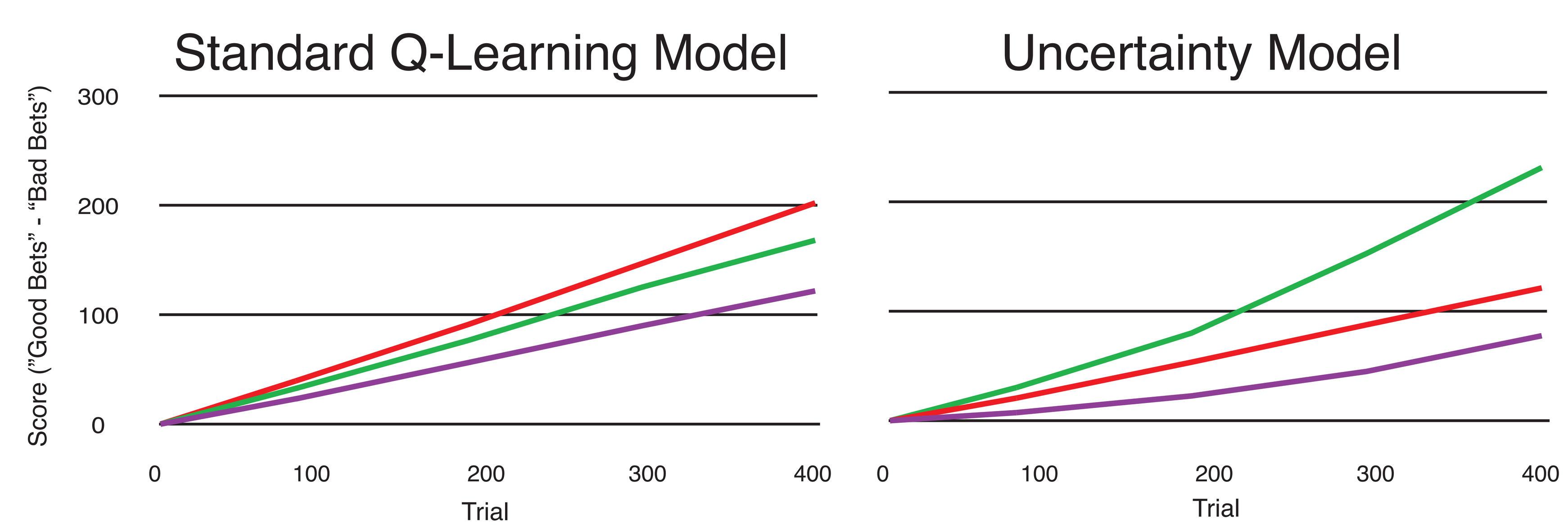
TFC plots were generated for activity from 4–10 Hz with 2.0 Hz/25 ms resolution, generated with BESA and averaged with Matlab.

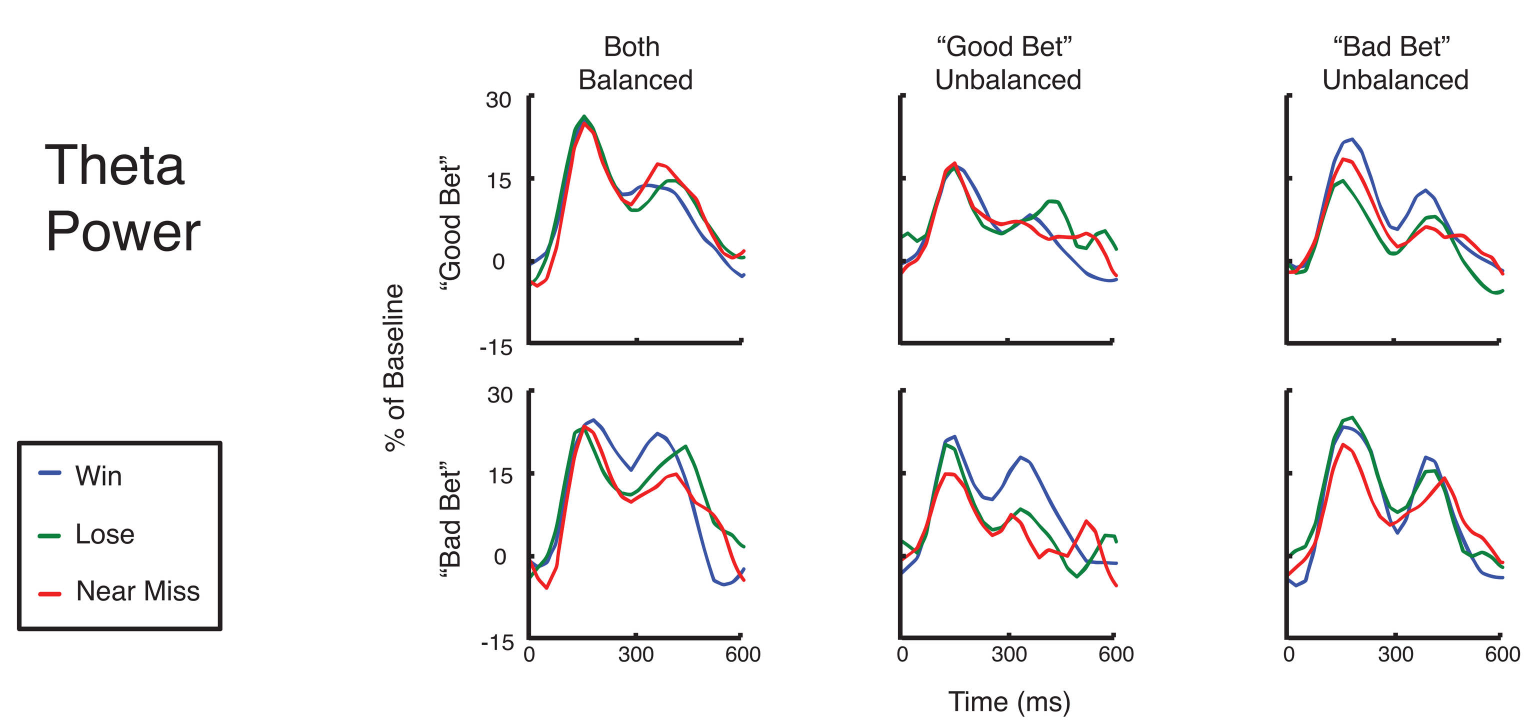
The Task



Results







Reinforcement Learning Model

The standard Q-learning softmax model did not predict observed patterns of behaviour. The best fit was obtained after inclusion of a dynamic "uncertainty" parameter. This parameter increased stochastic choice amongst the bet options dependent on the variance of prediction error.

Step 1: Determine Expected Value

Q-Learning

Estimated Action Value = Last Action Value + Learning Rate [Prediction Error]

$$Q_a(t+1) = Q_a(t) + \alpha_i[\text{reward}(t) - Q_a(t)]$$

Step 2: Explore or Exploit

Uncertainty Index

$$\Delta U(t+1) = U(t) + \alpha_U[\text{reward}(t) - Q_a(t)]$$

SoftMax + Uncertainty

$$P_{Good}(t) = \frac{e^{(Q_{Good}(t)/\beta U(t))}}{e^{(Q_{Good}(t)/\beta U(t))} + e^{(Q_{Bad}(t)/\beta U(t))}}$$

Conclusions

- Processing the outcome of a bet on an EGM entails more than a simple win/lose distinction.
- Disproportionately high representation of near misses negatively affects performance on a simple gambling task.
- Near misses do not manipulate subjective valuation, but rather may increase stochastic choice by affecting internal estimates of outcome certainty.

References

[1](Reid, 1989) [2](Sutton & Barto, 1998) [3](Cavanagh et al, 2010)

Alberta Gambling Research Institute