The central aim of the project was to develop computational models of how individual decision-makers learn in real time to anticipate and take into account the risks and potential consequences of their actions. The main focus was on the medial prefrontal cortex (mPFC), an area of the brain known to signal mistakes as well as the level of difficulty or conflict facing the decision-maker. The research effort involved iteratively developing computational models and testing their predictions with fMRI, leading to further refinements of the model. The original goal of developing a model of risk prediction was achieved. Further effort yielded a more general model of how both good and bad potential consequences are learned and anticipated. The model predictions were validated by numerous behavioral and fMRI studies, and the effort also yielded an exact recursive model of hyperbolic temporal discounting. The results overall provide a new and relatively simple computational model of consequence prediction that accounts for and predicts a wide array of empirical data and is well-grounded in the known neurobiologically.
Computational Neural Models of Risk
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Executive summary

The central aim of the project was to develop computational models of how individual decision-makers learn in real time to anticipate and take into account the risks and potential consequences of their actions. The main focus was on the medial prefrontal cortex (mPFC), an area of the brain known to signal mistakes as well as the level of difficulty or conflict facing the decision-maker. The research effort involved iteratively developing computational models and testing their predictions with fMRI, leading to further refinements of the model. The original goal of developing a model of risk prediction was achieved. Further effort yielded a more general model of how both good and bad potential consequences are learned and anticipated. The model predictions were validated by numerous behavioral and fMRI studies, and the effort also yielded an exact recursive model of hyperbolic temporal discounting. The results overall provide a new and relatively simple computational model of consequence prediction that accounts for and predicts a wide array of empirical data and is well-grounded in the known neurobiologically.

Results

The effort began by using human fMRI to validate a prediction of the error likelihood computational model (Brown and Braver, 2005), finding that the medial prefrontal cortex (mPFC) signals the potential severity of adverse outcomes of an action, as well as the likelihood of adverse outcomes (Brown and Braver, 2007). This suggests an account of mPFC as signaling the risk associated with an action. A second fMRI study showed that these risk signals are specific to the particular context in which a decision is made (Krawitz et al., in preparation), and a modeling study further accounted for individual differences in risk-taking as reflecting the relative efficacy of learning signals due to mistakes (Brown and Braver, 2008). These studies fulfilled the original objectives of the project.

The PRO model. With the original objectives met, the project effort was expanded to include several additional goals. First, new fMRI evidence showed that mPFC signals the potential rewards as well as the potential risks of actions, and that these predictions compete at the neural level (Alexander and Brown, 2010a). This led to a generalization of the error likelihood model, namely that mPFC not only predicts the risks of an action but more generally predicts the probability of all potential outcomes of an action, both desirable and undesirable (Alexander and Brown, In Press). Subsequent project effort was devoted to developing a new computational neural model of mPFC to instantiate this hypothesis, and the model was able to capture a vast array of data from human behavior, fMRI, and ERP, as well as monkey single-unit neurophysiology (Alexander & Brown, In Prep). In essence, the model simulates how mPFC learns to predict the probable outcomes of planned actions, and these predictions are then compared against the actual outcomes. Any discrepancies between the predicted and actual outcomes provide an error signal that feeds back to refine the outcome predictions. This model is now called the predicted response outcome (PRO) model.

In its original form, the PRO model simulation was fairly complex. In the last year of the grant period, considerable effort was spent reworking the model to distill it down into its essence of a few equations that can still capture the vast range of data accounted for by the original simulation (Alexander and Brown, In Prep).

Testing the PRO model with fMRI. Armed with the PRO model, the effort expanded to simulate the model in new experimental paradigms and extract a series of a priori predictions.
A series of fMRI and behavioral studies were then designed to test the model predictions, and all fMRI results were consistent with the model predictions. It was found that error-related activation in mPFC can be reversed when error likelihood is high (Jessup et al., In Press), following the model prediction that mPFC signals a discrepancy of actual vs. expected outcomes, as distinct from a comparison of actual vs. intended outcomes. It was found that apparent response conflict-related activation in mPFC persists even when the task conditions are changed so that multiple responses are no longer in conflict with each other (Brown, 2009), consistent with the model account of greater activity due to predicting a greater number of impending action outcomes. Another study now shows that mPFC is sensitive to the timing as well as the valence of predicted outcomes (Forster and Brown, In Prep). Yet another study shows that mPFC has distinct functional subregions corresponding with specific model components (Nee, Kastner, and Brown, In Prep). In the course of testing model predictions, it was necessary to further develop methods of quantitatively fitting and testing model predictions directly with fMRI data. This led to another methods-based paper on hierarchical Bayesian methods of model selection criteria with respect to fMRI data (Ahn et al., revised).

**Recursive hyperbolic discounting model.** In the course of developing models of outcome prediction, the effort ran into a persistent issue in reinforcement learning theory. On the one hand, human and animal studies of intertemporal choice consistently show hyperbolic temporal discounting. On the other hand, existing recursive models and temporal difference learning models generally show exponential discounting. The effort was therefore further expanded to develop the first exact recursive model of hyperbolic temporal discounting, which now allows simple and accurate online simulations of animal and human choice behavior (Alexander and Brown, 2010b).

Overall, the effort achieved and went well beyond the original objectives. Some of the newer results are still in various stages of preparation and review, but the results lay a foundation of a neurobiologically grounded mathematical and computational theory of how individuals predict and take into account the potential outcomes of their decisions.

**Personnel supported**
- Joshua W. Brown, Ph.D. – PI
- William Alexander, Ph.D. – Post-Doc
- Adam Krawitz, Ph.D. – Post-Doc
- Derek Nee, Ph.D. – Post-Doc
- Woo-Young Ahn – Graduate student
- Rena Fukunaga – Graduate student
- Elizabeth Dinh – Research Assistant
- Sarah Forster – Graduate student
- Rich Lewis – Research Assistant

**Publications resulting from the grant:**

1. Forster SE, **Brown JW** (in preparation) Medial prefrontal cortex learns to predict the timing of action outcomes.
2. Alexander WH, **Brown JW** (in preparation) Think before you act: medial prefrontal cortex as a predictor of action consequences


Technology assists:

**Feb-Mar 2009:** On request, the PI shared some raw countermanding task data from Brown & Braver (2005) with Glenn Gunzelmann and Rick Moore at AFRL, who are extending it to studies and models of sleep deprivation effects on cognitive control functions.

Other interactions and presentations during the grant period:


- 6 -
References