CHAPTER 7

DECISION NEUROSCIENCE

Imaging the Brain's "Buy Button"

Angelina Jolie announced in the *New York Times* in 2013 that she had chosen to have an elective double mastectomy, even though she did not have cancer. She made this choice because of her family history of breast cancer (her mother had developed the disease in her 40s and died of it at 56) and because she carries a mutation in a particular gene (*BRCA1*) that puts her at high risk of breast cancer. Her doctors had estimated that she had an 87% chance of developing the disease at some point in her life. On the other hand, the surgery carries a small risk of death (less than 1%), and it's also possible to have complications that could reduce one's quality of life. What would you do in this situation?

Every day we make thousands of choices. Some of them are inconsequential—should I eat yogurt or eggs for breakfast this morning? Others are not very important in the short term, but might have consequences in the long term—should I take the stairs or the elevator to my office on the third floor? Others are life altering, like Jolie's choice to undergo major surgery now in order to avoid an uncertain risk of disease in the future. For many years, the way that we make these choices has been studied by economists and psychologists, who have developed powerful theories that can describe many aspects of how we make decisions. In the past two decades, a new field called *neuroeconomics* has emerged that has attempted to describe how

the brain makes these decisions, and neuroimaging has played a central role in the development of this new field.

Why Do We Choose What We Choose?

Let's say that I were to offer you a 50/50 chance to either win $25 or pay $13—would you take the chance? Most of the research into how we make decisions has studied these kinds of economic decisions, because they are relatively easy to study in the laboratory and because they are so important in our daily lives in modern society. The first aspect of an economic choice is the value of the different items being offered (which we call *prospects*). "Value" is one of those terms that we all intuitively know the meaning of, but providing a formal definition has long been a major challenge. We don't mean the numeric value or price; rather, we mean how much benefit you expect to get personally from the object or how much you want it, given what you already have. Economists came up with the term "utility" to describe the hidden quantity that drives us to want some things more than others. They tend to assume that while we can't measure this utility directly, we can infer it from the choices that a person makes; if I choose yogurt over eggs for breakfast, that implies that yogurt has greater utility for me than do eggs. If I am a rational decision maker, then I should always choose the outcome that has higher utility, because this should in theory satisfy me the most.

Another important aspect of a choice is how likely each of the outcomes is to occur. You would probably like a chance to win a new car, but you will be much more excited by a 50% chance than you will about a one-in-a-million chance. We can put together the probability and the face value of a prospect to compute the "expected value"—that is, how much would you expect to get on average if you took the gamble many times. For example, take the roulette wheel. A simple bet is that the ball will land on a specific square, which has a 1 in 38 chance of happening on an American roulette wheel, meaning that if you were to play many times you would expect to win about 2.6% of the time. If you win the gamble, you get paid 35 times the amount you laid down (plus keeping your original bet). If we multiply the probability of

winning by the amount that can be won betting $100, it comes out to about $95; that is, if you were to play roulette many times, you should expect to come out around 5% worse off than you started. The fact that casino games are rigged against the player should not be surprising to anyone—so why do people flock to casinos in such large numbers?

The realization that people don't make choices based simply on expected value is not new, and in fact it was first discussed by the mathematician Daniel Bernoulli in the 1700s. Bernoulli was particularly interested in the fact that we often get less and less pleasure as we get more and more of something; you might be willing to pay $2 for a candy bar, but you likely wouldn't want to pay $20 for 10 of them. This idea that utility decreases the more we have can explain some of the ways in which humans seem to be irrational. For example, say that a particularly generous billionaire were to give you a choice between two options: a 50/50 chance to win $10 million, or $2 million for sure. Very few of us would pick the uncertain gamble over the sure $2 million, even though the expected value of the gamble ($5 million) is much greater than that of the sure thing. Bernoulli's explanation for this would be that as the amount of money goes up, the amount of added pleasure (or "utility") that we get from each dollar decreases, so that the difference in pleasure between nothing and $2 million is greater than the difference between $2 million and $10 million. In fact, sometimes utility can actually go down with more money—as explained by the hip-hop artist The Notorious B.I.G.: "It's like the more money we come across, the more problems we see."[1]

A deep understanding of the ways in which humans often behave irrationally did not come about until the work of Israeli psychologists Daniel Kahneman and Amos Tversky.[2] Kahneman and Tversky demonstrated many new ways in which human behavior is at odds with the economic concept of the rational decision maker and developed a theory (called *prospect theory*) that remains one of the most powerful theories in the study of decision making. Kahneman won the Nobel Prize in Economics for this work in 2002; Tversky would have shared it with him had he not died of melanoma in 1996 at the age of 59. Prospect

theory takes the idea of expected utility but then adds several wrinkles, two of which are relevant to our discussion. First, they pointed out that the psychological impact of a loss is greater than the impact of the same amount of gain; losing $20 hurts more than gaining $20 feels good, a phenomenon they called "loss aversion." This explains why most of us would not accept a gamble that offered a 50/50 chance to either win $12 or lose $10; even though the expected value of the gamble is positive, the impact of the loss is magnified compared with the gain, by about a factor of two for the average person. Second, they demonstrated that people will often behave differently depending on how a choice is described (or, in their terminology, how it is "framed"); when an outcome is described in terms of avoiding a loss people are more likely to take risks, compared to the same outcome described in terms of a gain. This theory has had a major impact on economics and psychology, and, as we will see shortly, on neuroscience as well.

The Neuroscience of Choice

The ease with which we make choices in our daily lives belies the incredible complexity of the computations that our brain must perform to make those choices. However, a quick look at the problems in decision making that occur with brain damage make it clear just how fragile this machine really is. One of the most tragic diseases to affect decision making is frontotemporal dementia (FTD), a degenerative brain disease that in some cases can cause people to gradually start making terrible decisions as the disease progresses, and which generally comes on much earlier than Alzheimer's disease, often in one's 40s or 50s. Dr. Bruce Miller of the University of California at San Francisco has studied FTD for many years and has amassed a long list of case histories that show just how badly FTD can affect decision making, such as this one:

> Her husband notes increased risktaking over the last 2 years. She has had a number of driving tickets for careless driving, including such things as not stopping at stop signs and backing

> down a one-way street instead of going around the other way. These tickets have accumulated over the last 2 years to a degree that they are unable now to get her insurance changed due to the excessive number of driving tickets she has received. By her husband's report she will lose her license if she gets 1 more ticket. Other risk-taking behavior was seen several months ago during a camping trip when she insisted on exploring an out-of-reach waterfall. When her husband explained that it was too dangerous because of unpredictable surf and risk of drowning, she continued to speak about the waterfall and early one morning went to explore it without telling him. She ended up injuring herself pretty badly on the walk. The patient exhibits little insight into these behavioral changes. This patient was subsequently detained by the police after a shoplifting incident and since she was unable to communicate or follow instructions, she ended up on the ground in handcuffs.[3]

The choices that we study in the laboratory are rarely as consequential as these, but they do provide us a window into the brain's machinery for decision making. An example comes from a study that Sabrina Tom in my laboratory performed in collaboration with Craig Fox, a professor in the school of business at UCLA (I described this experiment briefly in chapter 3).[4] We wanted to examine how the brain computes simple choices like the 50/50 chances to win or lose money that I described in the previous section, and to test whether we could see evidence for the predictions of prospect theory in brain activity. We brought 16 volunteers to the MRI scanner and presented them with a large number of gambles where they could win some amount or lose some other amount with a 50/50 chance; the amount that they could win on each gamble varied from $10 to $40, and the amount they could lose varied from $5 to $20. On each trial, they were presented with one of these gambles and asked to tell us whether or not they would take the gamble. It's always a concern whether people will tell the truth in these situations, so we used a sort of economic truth serum. After subjects were finished with the experiment and came out of the MRI scanner, we randomly

selected three of the gambles that they had experienced and looked to see whether they had said that they would take the gamble. If they said yes, then we flipped a coin and played the gamble for real money. To make it seem even more real, we gave them $30 in cash a week prior to the scan, and then asked them to bring $60 in cash with them to the scan, which they would be gambling with during the scan. No one actually lost more than the $30 that we had given them (the average subject won $23), but this procedure made the subjects feel as though they were really gambling with their own money and gave us more confidence that we were seeing realistic patterns of decision making in the brain.

When we analyzed the fMRI data, what we found was that there were two areas that showed a striking pattern of response to gains and losses (see figure 7.1). One of them, the *ventromedial prefrontal cortex*, sits in the bottom ("ventral") and middle ("medial") part of the frontal lobe, just behind the bridge of the nose. The other, the *ventral striatum*, is part of a set of brain systems known as the *basal ganglia* that sits deep within the brain. Both of these are areas that neuroimaging has shown play a central role in decision making. In our study, what we saw when we analyzed the trial-by-trial brain activity was that activity in these areas went up as the amount that the subject could win increased, but went *down* as the amount that the subject could lose increased. One of the main goals of the study was to examine the relation between the brain's response to gains and the response to losses, and this is where we were able to establish a direct link between the predictions of prospect theory and the activity of the brain. In particular, prospect theory predicts that losses hurt more than gains feel good. In both of these areas, we saw that the amount that brain activity decreased for bigger losses was steeper than the amount that it increased for bigger gains; we called this "neural loss aversion" by analogy to the concept that Kahneman and Tversky had developed in their studies of behavior.

The final clincher was the relation between brain activity and the behavior of the individual subjects. Some of the subjects in the study were quite averse to losses (only accepting the gamble if they could win more than five times what they could lose),

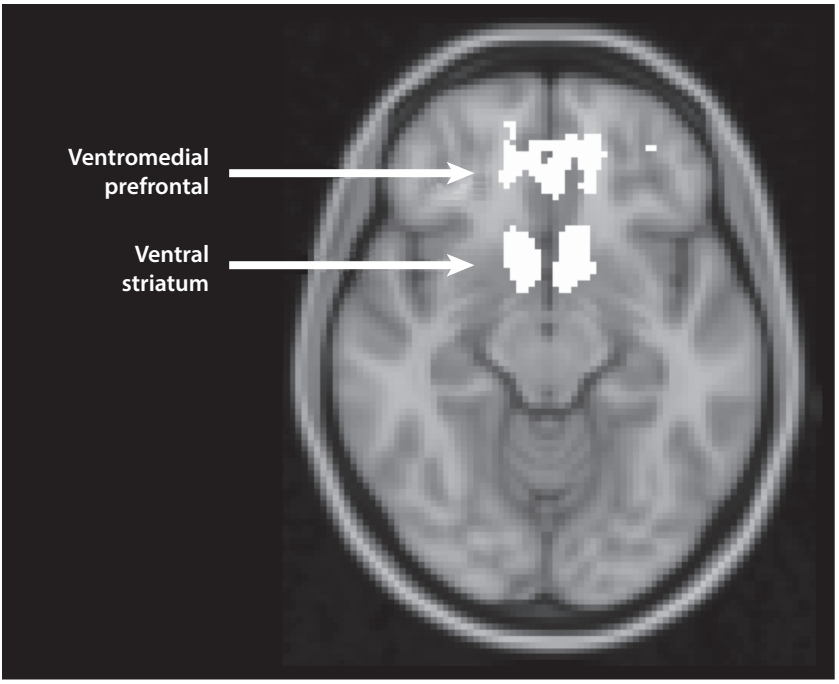

Figure 7.1. Results from our 2007 study of gambling decisions, showing (in white) regions in the ventral striatum and ventromedial prefrontal cortex that responded to increasing gains and decreasing losses.

whereas others just required that the amount they could win was larger than the potential loss by a small fraction. When we compared this to brain activity, we saw that the difference in brain responses to losses versus gains tracked the subjects' choices, such that people who were more averse to losses in their choices also had a larger difference between the response to losses versus gains in their brain. This study provided the first direct evidence from neuroscience in favor of prospect theory.

In science, replication is important before we truly believe a result, and that's particularly true in this study of 16 subjects, given the concerns about small samples that I discussed in chapter 6. Fortunately, the relationship between neural and behavioral loss aversion has since been replicated by a group of Italian researchers.[5] However, another one of the results from our study has not fared as well. Remember that we found several

areas in the brain whose activity turned down when the losses got bigger. We were also very interested in trying to find areas where the activity would turn *up* for bigger losses, since many researchers had proposed that thinking about losses should engage brain systems involved in fear or aversion. When we looked for regions whose activity went up with bigger losses, we found nothing. We looked especially hard in the amygdala, which is a region that many researchers had thought should be involved because of its longstanding association with fear and negative emotion (mentioned in chapter 1 and discussed further in chapter 8), but even with our fine-toothed comb we didn't see anything. The subsequent research has shown that we were probably wrong, having missed the signal owing to our lack of statistical power because of the small sample size. The Italian group found that activity in the amygdala did indeed go up when people entertained bigger losses, and other research by Benedetto De Martino and his colleagues at Caltech showed that individuals with damage to the amygdala—the same ones described in chapter 1 who don't experience fear—also didn't show the same level of loss aversion as healthy individuals. I think this is a great example of how individual studies may be right or wrong, but in general science tends toward the truth over time.

Learning What's Good

Several years ago, after almost 20 years of vegetarianism, my wife and I decided to start eating meat again. This left us with a huge landscape of new foods to try, but with little knowledge as to what we would actually like. Should we get the ribeye or the sirloin steak? Other than going by price, we were left asking the butcher, but often that doesn't really help so we ultimately had to take something home and try it out. Usually we liked what we got, but sometimes we didn't, and the next time we made sure not to buy that item again. On the other hand, if we really liked it then we were more likely to buy it again in the future. The ability to learn from trial and error in this way, which we call *reinforcement learning*, is fundamental to survival in the world and has long fascinated scientists. And, as I mentioned in chapter 1,

the neurotransmitter dopamine plays a critical role in this kind of learning.

Remember from chapter 1 that dopamine is transmitted broadly across the brain, and that it is released when we experience something that is better than we expected. Through evolution, our brains have learned to use this as a cue that whatever we just did we should probably do again in the future. In fact we now have a detailed understanding of exactly how this works. When we make decisions, there is a competition in our brain to determine which of the many possible actions we will choose, and this competition is centered around a brain circuit that connects the cerebral cortex to a set of deep brain regions called the *basal ganglia*. The strength of the connections between different neurons in the prefrontal cortex and the basal ganglia determines which specific action will be chosen in any circumstance; the stronger the connection, the more likely the action is to win the competition. It so happens that dopamine plays a central role in determining the strength of these connections, in a special version of the kind of Hebbian plasticity that we discussed in chapter 5: if neurons fire together in the presence of dopamine, their connections get stronger, while firing together in the absence of dopamine causes them to get weaker.

Because fMRI is only sensitive to blood flow, rather than to specific neurochemicals, we can't use it to measure dopamine directly. However, there is a lot of evidence that we can see the footsteps of dopamine in the fMRI signal. The first evidence came more than 15 years ago, when researchers found that fMRI signals in the basal ganglia showed a signature of the "reward prediction error" signal that I mentioned above. However, the definitive evidence relating dopamine to fMRI signals in the basal ganglia came from a study in rats by my colleagues Brian Knutson and Karl Deisseroth at Stanford.[6] They used a technique (pioneered in Deisseroth's lab) called *optogenetics*, which allows researchers to control the activity of specific sets of brain cells using light. This technique has revolutionized neuroscience, and will almost certainly win Deisseroth a Nobel Prize. What they did was to use the technique to selectively turn on the activity of the neurons that release dopamine, while the animal was being

scanned using fMRI in a tiny version of a human MRI scanner. When these neurons were turned on, releasing dopamine across the brain, they saw increased fMRI signals in several regions including the basal ganglia. This shows definitively that we can see dopamine signals in fMRI data, but remember the lesson of reverse inference: the fact that dopamine causes activity in the basal ganglia doesn't mean that activity in the basal ganglia *must* be due to dopamine, and in fact we are pretty sure that's not the case. This means that neuroimaging signals remain difficult to interpret in terms of their underlying biology.

Our understanding of reinforcement learning has also been greatly aided by computer scientists, who have long been interested in developing machines that can learn through trial and error. Computational models of reinforcement learning are generally based on the idea that we should change our "policy" (that is, the rules that determine how we will behave in certain circumstances) based on how far off our predictions are: bigger surprises should cause a bigger change in the policy. The model computes the value of each possible action in the world and then chooses which action to take at each point based on those values. It then updates its estimates of the values by changing them according to the amount of prediction error; for example, if I choose an action that predicts that I will get one unit of reward, and I end up getting two units of reward, then I will increase the value that I place on that action, which means that I will be more likely to choose it in the future. One of the major successes in the field of cognitive neuroscience, and in neuroeconomics in particular, has been the application of reinforcement learning models from computer science to the analysis of fMRI data, which lets us look for brain systems that respond in the way that is predicted by specific parts of the computational model. For example, we can apply the computational model to individual subjects' behavior as they are learning, and then use the model to estimate what the level of reward prediction error must have been for each choice. We can then look at which brain regions respond in a way that tracks this quantity. This kind of "model-based fMRI" has provided us with a whole new way to better understand what changes in activation actually mean, in terms

of the computations that the brain must be performing. It also forms the basis for the computational psychiatry approach that will be described in chapter 8.

Are We Really Two Minds in One?

Many thinkers about human behavior have appealed to a distinction between our rational minds and our "animal spirits." Speaking of the causes of instability in economic markets, the economist John Maynard Keynes said:

> Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than on a mathematical expectation, whether moral or hedonistic or economic. Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of animal spirits—of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.[7]

More recently, Daniel Kahneman has described this in terms of an impulsive and irrational "system 1" versus a slow and rational "system 2."[8] These stories certainly capture something correctly about human behavior, but I think that rather than reflecting the fact that there are truly two systems in the brain, they primarily reflect that humans are strongly drawn to thinking in dichotomies. The complexity of the brain is enormous, and it seems highly unlikely that any dichotomy will adequately describe it. Having said that, there is at least one such dichotomy that has gained substantial support from neuroscience, which is the distinction between habitual and goal-directed action.

Most of our behavior throughout the day happens without any mental reflection on the choice; we step our foot forward, speak linguistically correct sentences, and drive from the office to our home without having to consciously think about what is going to happen next. This is the power of habit, which is the term that we

use to describe actions that occur automatically without cognitive effort or intention. Without habits we would be paralyzed by choice, as noted by William James in the famous chapter on habit in his 1890 *Principles of Psychology*:

> The more of the details of our daily life we can hand over to the effortless custody of automatism, the more our higher powers of mind will be set free for their own proper work. There is no more miserable human being than one in whom nothing is habitual but indecision, and for whom the lighting of every cigar, the drinking of every cup, the time of rising and going to bed every day, and the beginning of every bit of work, are subjects of express volitional deliberation.[9]

An everyday example of the battle between habits and goal-directed actions occurs when we have to detour from a usual route in order to make an unexpected stop (say, at the dry cleaners on the way home from work). Many of us have had the experience of getting home and realizing that we were supposed to have made such a stop, but that we got distracted and habit took over. The nature of a goal-directed behavior is that it requires us to keep an end goal in mind; any distraction that causes the goal to be lost will probably prevent us from doing it. Just as habits are important to prevent paralysis by analysis, goal-directed behavior is equally important to allow us to transcend our usual routines and behave in adaptive ways when the world changes.

The economic model of decision making that we discussed above falls squarely in the domain of goal-directed decision: when we are making a choice, we think about how much we like each of the options and pick the one that we value the most. However, we all know that this fails to describe the process of how many of our decisions are actually made. When I go to the grocery store to buy a tub of yogurt, I don't look at all of the options and think about which one I want the most; I just grab a tub of the same Strauss Dairy plain yogurt that I have bought every week for the past few years. It's only when the world changes, such as when the store has run out of my favorite yogurt, that the goal-directed decision making kicks in. In a sense, this is perfectly rational: Why should I spend precious time thinking

about what to choose when I can just do what has always worked for me in the past?

The real problem comes about when those old choices no longer make sense, either because the world has changed or because you have changed. Back when I was a vegetarian, I had a serious M&M habit. Every afternoon I could be found at the candy machine, like a rat pressing a lever to get my daily ration. The main reason for changing my diet was the realization that a high-carb diet was not as good for my health as I thought it was, and over the course of about a year my mind-set about food and health completely changed. What didn't change was my craving for those M&Ms. Sometimes I am able to resist, but it's still the case that if someone sets a bowl of them in front of me, my new mind-set will be a weak match for my habit.

We discussed above how dopamine plays a role in learning about which actions are good and which are not, and this extends to the learning of habits as well. For example, people with Parkinson's disease, who have reduced levels of dopamine because their dopamine-producing cells are slowly dying, do not learn habits in the same way that healthy people do. We found a striking example of this a few years ago, when I collaborated with Daphna Shohamy and Mark Gluck at Rutgers University to study the way that people with Parkinson's disease learn a simple "weather prediction" task.[10] In the task, we showed the subjects sets of cards and asked them to learn by trial and error whether each set of cards predicted rain or sunshine. We made this difficult by giving them noisy feedback—for example, for one set of cards we might tell them that it predicted rain 75% of the time and sunshine 25% of the time. Our previous fMRI research had shown us that this task engages the basal ganglia when subjects are learning by trial and error, but not when they simply try to remember the outcomes without actually making choices.[11] We saw a parallel result when we tested people with Parkinson's disease on the task (without fMRI)—they were very bad at learning which cards predicted rain or sunshine when we asked them to learn by trial and error, but they were able to learn the same information as well as healthy subjects if we asked them to simply watch and learn without responding. This

finding fits with a long line of research that has shown that the brain systems involved in learning habits are distinct from those involved in conscious memory for events in the past, and tells us that dopamine is particularly important for the development of habits.

The flipside of this phenomenon can be seen in a bizarre side effect that sometimes occurs with a class of drugs that is used to treat Parkinson's disease and restless legs syndrome. These drugs, called "dopamine agonists" (known by trade names including Requip and Mirapex), trick the dopamine receptors in the brain into thinking that there is dopamine present. The drugs generally help with the symptoms of these diseases, but a small proportion of people taking these drugs started to report a very strange phenomenon: they suddenly became addicted, sometimes to obvious things like gambling, but in other cases to very odd compulsive behaviors. I once had a conversation on a flight to Los Angeles with an accomplished architect who had started taking one of these drugs to treat his Parkinson's disease and suddenly became addicted to gardening; he simply could not stop himself from spending all day in the yard. As soon as he stopped the drug, the insatiable urges to garden went away. This obsession was relatively benign, but many were not so lucky: a petition from the group Public Citizen (calling for a "black box" warning on these drugs) listed a number of cases where the outcomes were much more tragic, including a set of case studies reported by Kevin Klos and colleagues:

- Within six months of starting one of these drugs, a man who had never had any previous interest in pornography started buying pornographic films and having extramarital affairs. He also started gambling and lost hundreds of thousands of dollars, started overeating and gained fifty pounds in six months, and increased his smoking from one to two packs per day. All of these behaviors stopped within one month of stopping the drug, leading his wife to report "I have my old husband back."
- Another man became hypersexual within one month of starting the drug. Whereas they had previously had sex

> only once every few months, he suddenly demanded it several times per day. He also tried to pay a friend of his daughter to have sex with him, and requested that his son and daughter-in-law engage in group sex with him. This behavior resolved within a few months of stopping the drug.[12]

These cases show just how powerfully the dopamine system can drive people to engage in their worst impulses. We will discuss the relation between dopamine and habits further in chapter 8 when we discuss its role in drug addiction.

Now versus Later

Many choices that we make come down to a simple decision: Do you want something good now or something better later? When people put away money each month into a retirement account, they are making the decision to forgo spending some money this month so that they will be able to spend it (within compound interest) in the future. When I decide to have a piece of fruit rather than a chocolate flourless cake for dessert, I am trading off the immediate pleasure of the cake against my desire to be healthy in the future, not to mention my desire to not have to buy larger pants. We call these kinds of decisions "intertemporal choices," since they require making a choice between two different goods at two points in time, and they make up many of the most important choices in our lives.

There is an ongoing debate about how the brain accomplishes this kind of choice. One view, which has been championed by the neuroscientist Sam McClure of Arizona State University, is that there are two systems in our brain, much along the lines of Kahneman's system 1/system 2 distinction: an impatient emotionally based system that is constantly screaming "now!" and a more patient rationally driven system that nudges us to calmly consider the benefits of waiting. In McClure's first fMRI study of intertemporal choice, he presented subjects with choices between a smaller amount of money available sooner (for example, $5 today) and a larger amount available later

(say, $20 in six months) while he measured brain function using fMRI. When he compared activity between trials where the individual chose the immediate reward and those where the delayed reward was chosen, he saw that immediate choices were associated with more activity in a set of brain regions that by now will have become familiar: the ventral striatum and ventromedial prefrontal cortex, both strongly associated with reward processing. Conversely, choices of the delayed response were associated with greater activity in areas including the dorsolateral prefrontal cortex, which is thought to support top-down executive control over our decisions. The researchers concluded: "In economics, intertemporal choice has long been recognized as a domain in which, 'the passions' can have large sway in affecting our choices. Our findings lend support to this intuition."[13]

The intuition of passion battling it out with reason was not shared by Paul Glimcher. A professor at New York University, Paul was one of the early pioneers of the field of neuroeconomics, having done seminal work showing that the responses of single neurons in a monkey's brain are related to the value that the monkey places on stimuli in the world. Along with postdoctoral fellow Joe Kable, Glimcher set out to test a different way of thinking about intertemporal choice that was flavored by his years studying single neurons. One of the striking findings from the monkey studies is that one can often establish a close relationship between the activity of a single neuron and the behavior of an animal. This is known as a "psychometric-neurometric comparison"—with "psychometric" referring to the animal's decisions and "neurometric" referring to the activity of neurons. Previous research had shown that the relationship between these two can be very orderly, though those results came from studies of simple visual stimuli such as moving dots. However, if decisions are based on an underlying computation of value, then Kable and Glimcher expected that there should be brain areas in people where there is an orderly relationship between the person's subjective value of the option and his or her brain's response to this option—a psychometric-neurometric match. To measure this, they used an intertemporal choice task very similar to the one used by McClure, where people made

choices between a constant immediate amount ($20 today) and a range of larger delayed amounts at various delays.[14] They took a different approach to analyzing their data, which was to look for brain regions where there was a direct relationship between the person's subjective value for the delayed option (which they inferred from the subject's choices) and the brain's response across trials. They found that a psychometric-neurometric match was indeed present in some of the same areas that McClure's work had labeled as "impatient": the ventral striatum and ventromedial prefrontal cortex. In a knockout punch to McClure's hypothesis of dueling systems, they also analyzed their data using the same model that McClure had used and showed that their simpler model actually described the data better than McClure's model involving separate impatient and patient brain systems. These results convinced many researchers in the field that one doesn't need to appeal to a battle between passion and reason in order to explain how we sometimes are willing to wait for a bigger reward and sometimes simply want to take what we can get right away.

Another striking finding from the Kable and Glimcher study was that among their 10 subjects there were huge differences in the degree to which they discounted future rewards; some were incredibly patient while others wanted it all now. We all know intuitively that some people are better at waiting than others, and this ability seems to have an important impact on a person's ability to succeed in life. One of the best-known demonstrations of this comes from the "marshmallow study" by Walter Mischel and colleagues. In this test, children are taken into a room and shown two treats (such as a marshmallow and a cookie) by a researcher, and told that if they wait for the tester to return, they can have both treats, but if they decide that they don't want to wait they can ring a bell and have just one of the treats immediately. More than 500 children at the Bing Nursery School at Stanford were tested by Mischel and his colleagues in the late 1960s and early 1970s, who then followed them up over time to see how the ability to delay gratification was related to later outcomes in life. What they found was striking: the children who were better able to delay gratification were more academically

successful (performing better on the SAT years later) and were also described by their parents as being more academically and socially adept.[15]

B. J. Casey is one of the world's leading cognitive neuroscientists, and in 2011 she and her colleagues (including Walter Mischel) reported a study that gave us new insights into the differences in brain function between Mischel's patient and impatient kids. They followed up with a group of Mischel's children, roughly 40 years after they had been first tested, and were able to convince 27 of them to return to the lab for MRI scanning. They used a task that Casey has developed over many years of research, called a "go/no-go" task, in which subjects are shown some stimuli and have to respond to most of them but occasionally withhold their response (the same task used by Kent Kiehl in the neuroprediction study mentioned in chapter 6); in this case, the stimuli were happy or fearful faces, and the subject had to respond to one emotion but withhold his or her response to the other. We know from previous research from my lab and many others that when people stop themselves from making a response, a network of brain regions is activated that centers on a region in the right prefrontal cortex called the inferior frontal gyrus.[16] When Casey compared her subjects who had been good delayers to those who had been poor delayers, she saw that the poor delayers were worse at stopping themselves (making more errors when they were supposed to withhold their response), and that their inferior frontal gyrus was less active than the good delayers. This is an exciting finding that shows the echoes of early childhood behavior decades down the road, but it's worth noting that the ultimate sample was very small (with only 15 high-delaying individuals and 11 low-delayers), so we need to interpret the results with caution and wait for other larger studies to replicate this finding.

The Advent of "Consumer Neuroscience"

It was really only a matter of time until neuroeconomics caught the attention of people whose job it is to more effectively sell us things. With billions of dollars at stake, even tiny improvements

in the market share of a product can translate into huge sums of money. The potential of "neuromarketing" (or, as its advocates now call it, "consumer neuroscience") was first made clear in a 2004 study by Sam McClure and Read Montague, which has become widely known as the "Coke/Pepsi study."[17] McClure was interested in understanding how brand information changes the brain's response to a food, and cola drinks are a particularly interesting example because it has long been known that people's stated brand preferences often don't match their choices in a blind taste test. To test this, McClure first asked people which brand they preferred, and then also gave them a blind taste test—indeed, there was very little relation between the brand that people said they preferred and what they chose in the blind taste test. He then used a custom device to deliver soda to people while they were being scanned using fMRI, which let him measure the brain's response to these drinks either with or without knowledge of the brand. He focused on the ventromedial prefrontal cortex, which you will remember from earlier as one of the areas that shows a strong response to rewards. When people were delivered drinks without any brand information, the response in this area turned up in direct relation with how much the person said he or she liked the drink.

What about the effect of knowing the brand? It turned out that the Coke brand was stronger than the Pepsi brand, which could be seen both in behavior and in the brain. In a taste test where people were given the chance to drink Coke versus an unlabeled drink that they were told could be either Coke or Pepsi, people were more likely to choose Coke; however, in the same experiment done with Pepsi, there was no effect of the brand on people's choices. fMRI showed that there was more activity in several brain areas when people received branded Coke compared to Coke without the brand information, including the dorsolateral prefrontal cortex, which seems to play a role in exerting top-down effects on our fundamental desires; here, too, no differences were found for Pepsi. This study provided the first suggestion that it might be possible to use neuroimaging to identify the effects of marketing information.

Several years after the Coke/Pepsi study, one of the first proclamations of the power of neuromarketing appeared in one of my favorite sources for overblown junk science: the *New York Times* op-ed pages. A team of cognitive neuroscience researchers from UCLA (including Marco Iacoboni, who was also behind the "Your Brain on Hillary" debacle discussed in chapter 1) used fMRI with television ads presented during the 2006 Super Bowl in order to see how five viewers' brains would respond to them. Later that evening, Iacoboni had already picked the winning and losing ads based on how much activation they caused in areas thought to be related to emotion, empathy, and reward:

> Who won the Super Bowl ads competition? If a good indicator of a successful ad is activity in brain areas concerned with reward and empathy, two winners seem to be the "I am going to Disney" ad and the Bud "office" ad. In contrast, two big floppers seem to be the Bud "secret fridge" ad and the Aleve ad. What is quite surprising, is the strong disconnect that can be seen between what people say and what their brain activity seem to suggest. In some cases, people singled out ads that elicited very little brain responses in emotional, reward-related, and empathy-related areas.
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> Among the ads that seem relatively successful, I want to single out the Michelob ad. Above is a picture showing the brain activation associated with the ad [*not shown here*]. What is interesting is the strong response—indicated by the arrow—in "mirror neuron" areas, premotor areas active when you make an action and when you see somebody else making the same action. The activity in these areas may represent some form of empathic response. Or, given that these areas are also premotor areas for mouth movements, it may represent the simulated action of drinking a beer elicited in viewers by the ad. Whatever it is, it seems a good brain response to the ad.[18]

If this book has done its job so far then your hackles should be on end, as this is a prime example of reverse inference gone wild. The second paragraph of the quote makes that abundantly clear: He tells us that there is activity in the "mirror neuron" areas

of the brain, which could have to do with empathy, but could also have to do with simulated mouth movements. In this case interpreting fMRI results seems to be more akin to a Rorshach test (identifying what the interpreter already believes) than to actual science.

Several years later, the *New York Times* op-ed page once again published overblown neuromarketing claims, this time by self-proclaimed "neuromarketer" Martin Lindstrom in an article titled "You Love Your iPhone. Literally."

> Earlier this year, I carried out an fMRI experiment to find out whether iPhones were really, truly addictive, no less so than alcohol, cocaine, shopping or video games. In conjunction with the San Diego-based firm MindSign Neuromarketing, I enlisted eight men and eight women between the ages of 18 and 25. Our 16 subjects were exposed separately to audio and to video of a ringing and vibrating iPhone . . . most striking of all was the flurry of activation in the insular cortex of the brain, which is associated with feelings of love and compassion. The subjects' brains responded to the sound of their phones as they would respond to the presence or proximity of a girlfriend, boyfriend or family member. In short, the subjects didn't demonstrate the classic brain-based signs of addiction. Instead, they loved their iPhones.[19]

If Lindstrom is correct, then activation in the insular cortex of the brain provides a neuroscientific "love meter." Unfortunately this is simply incorrect, as I and 44 colleagues pointed out in a letter to the editor of the *New York Times*:

> "You Love Your iPhone. Literally," by Martin Lindstrom (Op-Ed, Oct. 1), purports to show, using brain imaging, that our attachment to digital devices reflects not addiction but instead the same kind of emotion that we feel for human loved ones. However, the evidence the writer presents does not show this. The brain region that he points to as being "associated with feelings of love and compassion" (the insular cortex) is active in as many as one-third of all brain imaging studies. Further, in studies of decision making the insular cortex is more often

> associated with negative than positive emotions. The kind of reasoning that Mr. Lindstrom uses is well known to be flawed, because there is rarely a one-to-one mapping between any brain region and a single mental state; insular cortex activity could reflect one or more of several psychological processes. We find it surprising that The Times would publish claims like this that lack scientific validity.[20]

Marketers continue to regularly make overly strong claims about the power of neuroscience methods. To combat this, Joe Devlin of University College London came up with a list of warning signs for what he calls "neuromarketing snake oil." The first warning sign, "Beware claims of mind reading," is in line with the point made throughout this book that there is no simple one-to-one mapping between psychological states and brain activity. Another warning sign is "Beware proprietary data analysis techniques." While it might seem that neuromarketers could use their substantial financial resources to come up with better ways to analyze data, in reality such claims are usually a cover for untested methods with unknown reliability. Others include being on the lookout for "neuro-sophisms and neuro-myths" as well as for "quack neuroscientists" with seemingly impressive titles like "Chief Neuroscientist." More generally, it's important when reading about scientific research of any kind to be sensitive to overselling and oversimplification—if it seems like you are being given a sales pitch, then you probably are, and that's usually not the sign of solid research.

In the wake of these ham-handed early efforts to establish neuroscience as a tool for marketing, a growing group of researchers is taking a more careful and reasoned approach to investigate whether neuroscience is actually worthwhile for understanding consumer behavior. One of the leaders of this group has been Vinod Venkatraman, a marketing researcher at Temple University who has undertaken one of the most systematic examinations of the effectiveness of various neuroscience tools for marketing purposes.[21] Alongside standard marketing questionnaires about how much people liked each of several products, he and his colleagues tested a number of different methods, including fMRI and EEG along with other measures

meant to measure physiological responses (such as heart rate measurement) and psychological measures meant to measure implicit attitudes. They measured the response to each of a large number of ads, and then used data on real-world advertising effectiveness to determine which methods were best at predicting the effectiveness of the ad campaigns. Their results showed that fMRI (in particular, response in the ventral striatum to the ads) was far more effective than the other methods at predicting ad effectiveness, improving the accuracy of the predictions by more than 50%. The improved effectiveness of fMRI may reflect the fact that the response of the ventral striatum is either more sensitive to the features of products that drive people to want them, and/or that these responses are less sensitive to other factors that can cause psychological measures to be unreliable. This kind of careful work shows that there is indeed promise in the application of neuroscience to marketing questions.

Reading the Collective Mind

The ability to predict the behavior of an entire population based on the brain activity of a few people is the holy grail of a number of fields, such as consumer neuroscience and neuropolitics, and new research has started to suggest that it might actually work. One of the leaders in this field is Emily Falk, who is now a professor of communication at the University of Pennsylvania. She has pioneered the idea of the "neural focus group," in which fMRI is used to predict how people will respond to an advertisement at the population level. In her first study to examine the effectiveness of the neural focus group, she used fMRI to predict responses to an antismoking campaign for the US National Cancer Institute's quitline (1-800-QUIT-NOW).[22] Subjects viewed a set of television advertisements during scanning, which were taken from three different advertising campaigns. The subjects also answered a questionnaire about how effective they thought the ads were, which is what the standard focus group would do. Falk examined brain activity evoked by each ad within the ventromedial prefrontal cortex; this is the same area that we previously discussed in the context of decision making, whose

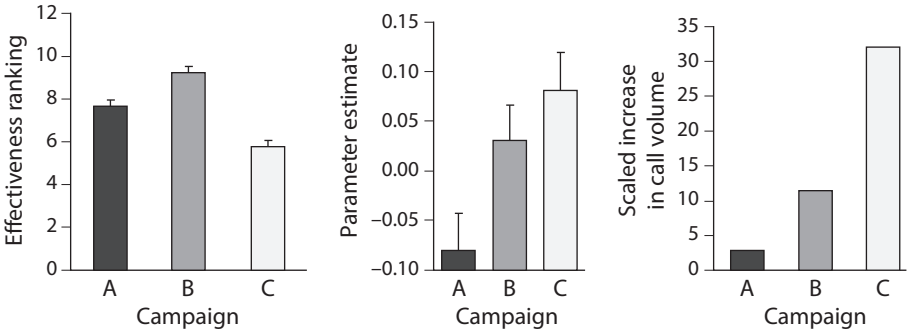

Figure 7.2. Results from Emily Falk's neural focus group study. The *left panel* shows how effective the subjects rated each ad; they thought that the ads from campaign B were the most effective. The *middle panel* shows the average brain response to ads from each campaign; the response to ads from campaign C was largest. The *right panel* shows the actual call volume to the quitline after each campaign, which followed the brain response rather than the subjects' survey responses. From Emily B. Falk, Elliot T. Berkman, and Matthew D. Lieberman, "From Neural Responses to Population Behavior," *Psychological Science* 23, no. 5 (2012): 439–45, copyright ©2012 by Emily Falk. Reprinted by permission of SAGE Publications, Inc.

activity generally increases in response to stimuli that individuals value positively. She and her colleagues then pitted the results from this "neural focus group" against the standard survey group by comparing the results from both to a very different real-world outcome: the volume of phone calls to the quitline in the month following the introduction of each ad campaign. The results (shown in figure 7.2) were striking: the brain responses of the 30 subjects correctly predicted which ad campaign would be most effective, while the standard focus group responses did not.

The idea of the neural focus group inspired my colleague Brian Knutson and his student Alex Genevsky to ask an even harder question. They were interested in understanding how people make decisions on the microlending website Kiva, in which individuals from low-income countries post requests for funding of their small businesses. One of the major benefits of analyzing the Kiva site is that it allows researchers to obtain extensive data automatically, providing the ability to assess a large number of lending decisions; Genevsky and Knutson used this to obtain data on almost 14,000 decisions, half of which were decisions to lend and the other half were decisions not to lend.[23]

They first asked whether they could predict lending decisions based on the features of the photo of the individual requesting funding or the description of the loan request. Because it would have been very difficult for one person to sit down and rate the features of so many photos, they instead used a tool that has become a mainstay of psychological research: Amazon's Mechanical Turk (known among researchers as "MTurk"). MTurk is an online marketplace for workers to complete web-based tasks. Individuals (known as "Turkers") are able to choose among a large number of tasks, each of which offers to pay a certain amount of money for a certain amount of work. In this case, each Turker was presented with one of the photos and asked to rate its visual clarity as well as what emotion the person was displaying. Using these data alongside the data obtained from the Kiva site, Genevsky and Knutson were able to show that one can successfully predict which loan requests will be successful based on several features of the photo, including the sex of the requester (women were more successful than men), the clarity of the image, and the amount of positive emotion portrayed by the requester in the photo. The accuracy was not earth-shattering—knowing just the amount of positive emotion in the image, they could predict about 17% of the variability in Internet lending rates, which is better than guessing but far from perfect.

They next asked whether the brain responses of a neural focus group could help improve prediction. They chose 80 requests that had the most extreme ratings of positive or negative emotion from the large set rated by the Turkers, and then presented these to subjects during fMRI scanning while they made lending decisions about each request. When they compared activity between loans that subjects funded and those that they didn't, there was activity in the ventral striatum and ventromedial prefrontal cortex, two regions that we have seen repeatedly to relate to subjective preferences. They quantified the response in the ventral striatum, which, as we have seen, is often associated with reward processing. Using just the fMRI data (see figure 7.3), they were able to account for about 6% of the variability in lending rates; note that while this is better than nothing, it's substantially less than one could predict using just

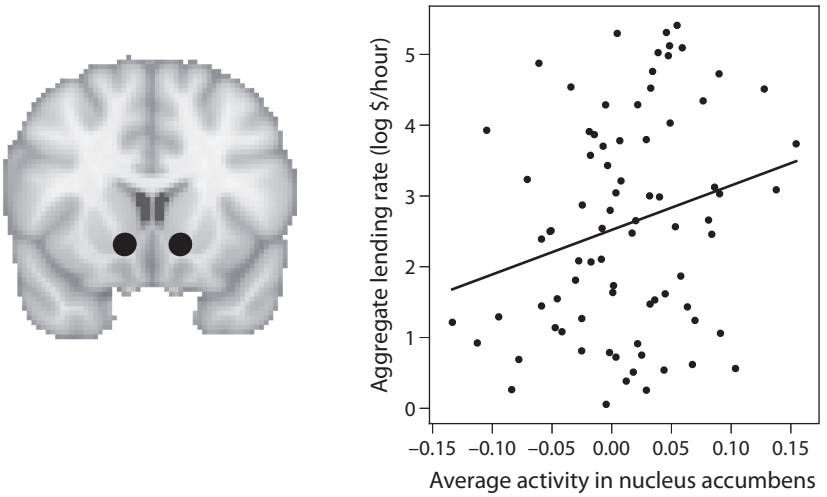

Figure 7.3. Results from the neural focus group study by Alex Genevsky and Brian Knutson. The *left panel* shows the location (in black) of their regions of interest within a part of the ventral striatum called the nucleus accumbens. The *right panel* shows the relationship between activity in the region of interest that was evoked by each request, and the amount of lending that each request received on Kiva, with the best fitting line showing the average relationship between the two. Generated using data generously provided by Alex Genevsky and Brian Knutson.

the photo ratings. Putting together the photo ratings and the fMRI data, they were able to reach a prediction accuracy of 20% of the variance, showing that combining the photo ratings and fMRI data was better than either alone.

We don't know whether marketing companies are currently using neural focus groups, but it's a pretty good bet that they are. Even though the levels of prediction accuracy are often only slightly better than guessing, these small improvements could still lead to big financial gains if they improve sales even just a tiny bit. We still need more data in order to understand just how generalizable these results are—for example, do they only work with ads involving photos of people?—but it's almost certain that these questions are currently being asked by consumer neuroscientists and will play an increasingly important role in advertising, politics, and other areas where public opinion is important for decision making.

The degree of interest in neuroscience within the business world is evident in the fact that many major business schools have hired faculty who engage in neuroscience research, including Harvard, Stanford, and the University of Chicago. The Wharton School of Business at the University of Pennsylvania has started the Wharton Initiative in Neuroscience, which is assembling a set of researchers dedicated to "building better business through brain science." To run this initiative they tapped Michael Platt, a neuroscientist who had spent most of his career studying decision making in monkeys and who had collaborated with Paul Glimcher on some of the earliest studies of value-based decision making in monkeys. The interest is also evident in the fact that Nielsen, the premier market research company in the United States, has established a consumer neuroscience team of almost 20 researchers, whose job it is to figure out how to use neuroscience to improve market research. The interplay between neuroscience and business shows no signs of stopping.