Brain and Mind
May 14, 2004

William T. Newsome, PhD
Decision Making and the Neural Representation of Value

Introduction by David Cohen

David Cohen: Well that was a spellbinder. Nancy, you'll have to come back and update us annually. I think this is a comment the way many of us have felt almost every talk in this symposium.

Our next speaker is Dr. William Newsome. He's a professor in the Department of Neurobiology at Stanford and a Howard Hughes Institute investigator at Stanford. He received his undergraduate degree from Stetson University and his PhD from the California Institute of Technology.

He began his faculty career at the SUNY, Stonybrook, in the Department of Neurobiology and Behavior, and at this point I think it's probably fitting that I shift from calling him Dr. Newsome to Bill, since I was the chair who recruited him to Stonybrook for his first position. Unfortunately the department lost him in 1988 when he went to Stanford, and I think it was in no small measure because Bill and his wife, Zondra, never could acquire Long Island as a second language.

Bill has been particularly courageous in tackling especially challenging research problems, challenging both conceptually and technically, problems in visual perception and cognition. He's been extraordinarily innovative in devising behavioral paradigms which combined with single-cell recording to address questions about deep levels of visual perception, decision making, and the role of value in decision making. He's appropriately collected the expected array of awards, including the Rank Prize in Optoelectronics, the Spencer Award from Columbia University for highly original contributions to neurobiology, [and] the Distinguished Contribution Award from the American Psychological Association. Most recently he's been invited to deliver the 13th annual Marr Lecture at Cambridge University, and the King Solomon Lectures at Hebrew University in Jerusalem. And I think you're on your way to that, aren't you, Bill? Bill was elected to membership in the National Academy in 2000. And it's with some nostalgia and some pride in my recruiting taste that I'm indeed pleased to be able to present Bill Newsome who will speak on "Decision Making and the Neural Representation of Value."
Internal Representation of Value

William Newsome: Thank you, David, for the introduction and for that first job, which of course is extremely important.

So I'm going to be talking today about decision making and the neural representation of value, and many of you have seen this title and wondered what the hell is he going to talk about? And one day neuroscience, hopefully, will get to the point where we can talk about ethical values and higher values of humans and how we arrive at those things, but I'll be talking about something more mundane today, which is value in the economic term. Okay? So we're all seeking constantly to maximize return on our investments, right? So many of you had a decision to make a few moments ago, which was whether to stay here and listen to this talk or whether to go outside and enjoy the morning. And you did some calculations about value and potential return on your investment in time, and fortunately for me most of you decided to stay. And I'm hoping that I won't disappoint you in that decision. Some people, however, resonated with David Cohen's lovely Freudian slip this morning when he talked about this "oppressive lineup of speakers" for the symposium, and they're out enjoying the morning. And my best wishes are with them.

I want to say before I start that all of the work that I'll talk about today is a collaborative venture between myself and two extremely talented graduate students in my lab, Leo Sugrue and Greg Corrado, so when I say we, those are the guys that I'm talking about in addition to myself.

Okay, so let's talk a little bit about this value thing and how we got into it. My lab, as David alluded to, we've studied visual perception, have fifteen, twenty years on the books studying visual perception, which led us naturally to a study of decision mechanisms that we've been working on, simple forms of decision making in primates we've been working on for the last—really intensively—for the last five to seven years. And this little diagram here shows you the classic sensory physiologist's view of decision making, and I am a sensory physiologist. So there's a world out there that provides sensory input to the brain, and there are sensory systems in the brain that analyze that world—in Richard Axel's phrase yesterday "deconstructs that world"—and loads a representation in sensory areas of the cortex, and then ultimately at some higher level of the cortex, decisions have to be made about what's out there: Is it predator, is it prey? And of course those decisions that get made influence your motor-output structures. If it's predator, you're likely to run or fight; if it's prey, you're likely to get ready to pursue and hopefully have some hunger satisfied or something like that. So in this sensory physiologist's view of the world, decision mechanisms follow directly upon the sensory input. But economists and psychologists have known for a long, long time that this is a highly impoverished view of decision making, and that there are internal representations within the brain of value, the likely value, of certain
outcomes and certain actions that we all take, and these internal representations of value influence decisions just as much as does the sensory input, and sometimes more so.

So one of my favorite examples like this is a trout fisherman going out to fish in the stream early in the morning, top of the morning. He's got a decision to make: which pool do I cast my fly into, which rock do I stand on? And the sensory evidence here is really rather weak because, after all, he can't see the fish, they're down there under the surface of the water, right? So how does he decide? And the answer is he decides because he has some internal representation of value. Where on this stream this time of morning at this time of year have I had luck in the past? In other words, he has a reward history of trial and error and where he's been rewarded or failed to have been rewarded, and that history that all of us are carrying around with us all the time influences these internal representations of value which in turn influence the decisions that we make.

Now, for a person who studies the brain if you're interested in decisions, it's obviously extremely important to bring this under control and start being able to see physiologically how these internal representations of value work and how they influence decisions. But this is a difficult thing to do in a laboratory, this is rather hairy. If I'm a sensory physiologist and I'm studying vision, I have a place to stand. I stand on the sensory input. I can present a particular visual stimulus to a human subject or to an animal subject time after time after time, the way that Nancy just described for you, and I can see what areas of the brain or what cells in the brain have activity that's correlated with that stimulus. If I'm a motor physiologist, I can train a human subject or an animal subject to reproducibly output motor behavior over and over again, and I can see what sorts of activity in the brain correlates with that motor output. But how in the world are we going to bring this under control, the sort of stimulus, action and value?

**The Matching Paradigm**

Okay, so that's the first question that we've got to answer here. And the short answer is that we are not going to have to reinvent this wheel, that there is a group of psychologists who've worked long and hard in the 1950s and 1960s, Richard Herrnstein and his colleagues, to establish what they call the matching law as a way to assess an animal's evaluation of stimuli. So the notion of the matching law that Herrnstein worked . . . he worked largely with pigeons, okay, and the pigeons had a choice of which lever to peck, lever A or lever B, so they had a choice, it was a free-choice paradigm. And the law says that animals allocate time or responses among competing behaviors in proportion to their relative frequency of reinforcement. So you can put this little equation down which just says the response on lever 1 divided by the total responses—so that's just the proportion of responses on lever 1—is equal to the proportion of the time that the animal gets rewarded for pressing lever 1. Now the good news here is that this reward fraction is under experimental control. Herrnstein could control this, right? So he can
program his computer to decide how likely the animal is to get rewarded when he presses lever 1 versus how likely he is it get rewarded from pressing lever 2. And here he's manipulating the percentage of reinforcements on key A, all the way from zero, which means that key B gets rewarded all the time, up to one hundred, which means that key A gets rewarded all the time. And this shows you data from three pigeons—how frequently the pigeons responded on key A—and you can see that there's this nice linear relationship—these pigeons are obeying the matching law very nicely so that when they get rewarded infrequently on key A, they choose key A infrequently. And when they get rewarded frequently they choose key A frequently.

Now Herrnstein's brilliant insight here was that this kind of behavior . . . if an animal actually matches, now we have a behavioral handle on value because we can use the responses, the proportion of responses, that the animal makes, that's under his control, that's under the animal's control, and we can measure it, and we can use that as an index, a proxy if you will, for these internal valuations—how the animal's valuing the likely outcome of these two choices.

So we have adopted this matching paradigm to use in our laboratory, and I'm just going to give you here over the next half hour an insight into the way that systems neuroscientists like myself think about these problems, and the way that we try to approach these problems in the laboratory. Now I'm going to be talking about this value thing, but the basic plot is the same whether we're talking about visual perception, attention, memory, decision making. If you get the gist, the hang of the way we think and do things here, you can then apply this to all sorts of other sort of cognitive situations.

The first thing is that work in my field always starts with behavior. I've already outlined for you behavior, a central behavioral question. So we believe in this field that the brain's primary function is to produce intelligent and interesting behavior, okay? So our questions always start with behavior, and I've already posed for you a behavioral question about value. And we are going to talk now when we discuss this matching paradigm about how we measure value rigorously at the behavioral level. Then we also bring theory to bear. And we in the theory, we're going to say can we formally describe—and by formally I'm actually talking about mathematically—describe how value is computed within the brain; i.e., can we build a model? We're going to try to build a model that actually duplicates the animal's choice-making behavior. And then finally we're going to address some physiological questions, we're going to say what are the neural circuits within the brain that implement this computation?

And this is relatively new work in my lab. The first paper has just been accepted for publication, actually, it's not yet published but will be very soon, and so you should regard this as a progress report. These questions are not completely answered at this point in time, but again, David, have me back in five years and we'll see what happens.
Matching Experiments in Rhesus Monkeys

Okay. One little aside before I go forward. All of the experiments that I'm going to talk to you about today are done in rhesus monkeys—awake, behaving monkeys—who actually perform a task and we measure their brain activity while they're performing the task. Now there are some kinds of neurobiological questions that are very important, such as the one Rod MacKinnon talked about yesterday, that you don't actually have to have an animal on line to do. You can work in tissue culture, you can work all sorts of different reduced preparations. But those of us who study the nervous system and want to understand how the nervous system produces intelligent behavior have to use an awake, behaving nervous system while it's actually in the process of producing behavior, right? There's only a limited amount you could learn about a car engine without the car engine actually in action and doing its thing. If the car's just sitting there turned off you can make all kinds of theories, but how do you test them? Well you've got to make manipulations and crank that car up and see if it works. Well it's the same thing in studying the nervous system, and we actually have to work in a functioning nervous system.

Now there are some things you can do in simpler nervous systems. As Eric Kandel showed us yesterday this inelegant little animal, *Aplysia californica*, can actually perform remarkable memory feats, and Eric has been enormously successful in unraveling some of the circuitry underlying memory in *Aplysia californica*. People work in rodents frequently because rodents are good spatial navigators and they're good olfactory discriminators. So there are some things that different organisms are good at. But by far and away the most cognitively versatile animals that we can actually bring into the laboratory and do experiments with are monkeys, which is why we work with our rhesus monkeys. And I'll have more to say about that in just a moment.

Okay. So our first task here is behavior. We're going to the matching law, we're going to train monkeys on a matching task, an ocular-motor matching task, so they're going to use their eyes to do this matching thing, and that's deliberately chosen because the ocular motor system, the motor system that controls the eyes, is the best-known motor system in the primate brain, so we can take advantage of lots of background work. Okay, now I'm going to describe the task for you right now, and you have got to hang with me here, okay, because if you don't understand this task the rest of the time you'll have higher value out with a cup of coffee and enjoying the morning, okay? So follow this task for me now.

So an animal sitting in the primate chair, and the animal comes out and does this every morning so he's utterly accustomed to this sort of thing, and he looks at a TV screen in front of him, and we have him playing this little economic matching game. An animal sitting in the midst of an apparatus called the scleral search coil apparatus that allows us to measure his eye position extremely accurately at any instant in time. So our computer knows from millisecond to millisecond exactly
where this animal's pointing his eyes. The first thing that happens is the little fixation point comes on the TV screen, and the monkey has to look at it, and that lasts for about 300 milliseconds. After 300 milliseconds two targets come on, a red target and a green target, and ultimately the monkey's going to move his eyes to one of these two targets. But first of all there's this little delay period. The red and the green come on and there's a delay period that's variable in length from one to two seconds. So one thousand one, one thousand two, and after that delay period the fixation point dims and the monkey then moves his eyes to one of these targets or the other target and he either gets rewarded or more often he does not get rewarded, and I'll tell you about that in just a moment, and then he holds his eyes on that target that he has selected for two to four hundred milliseconds, and then the fixation point turns bright again and he moves his eyes from the target back to the fixation point, okay, so that's finished with one trial, he's made one choice. And then these two red and green targets may be rerandomized spatially, if you watch carefully they're going to switch positions, there they go, and then we just come back to this point here, okay, and we start all over again. So he has to wait one to two seconds, he makes a choice, and so on and so on, and he just goes around in this circle making eye movement after eye movement, choosing the red target or the green target. Okay?

Now the critical thing is, How does he get rewarded? So the monkeys are thirsty when they come out to work in the morning, and they'll sit here and work for this sort of thing because they're going to get a shot of juice, or sometimes it's Kool-Aid, we find what they like the best, and they'll sit here and do this thing for a couple or three hours while we acquire behavioral data and electrophysiological data, so they're highly motivated to get these rewards, and they'll sit here and go in this loop, making eye movement after eye movement. Now here's the critical thing, here's where the economic and the value and the matching comes in, is, How do they get rewarded? All right. Now what you have to do, you have to imagine that there's a little stopwatch attached to each one of these two targets; there's a red watch attached to the red target and a green one attached to the green target, and these guys are counting down, and on average the red one's going to count down to zero once every 10 seconds, and on average the green one's going to count down to zero once every 30 seconds. And when those clocks count down a reward becomes available. And the very next eye movement that the animal makes to that color he picks up a reward. All right.

Now it's important to realize that these clocks are independent. They're not synchronized to each other at all; it's independent things going on on the two colors, and the times, the actual times, are a Poisson process—that means they're random. And this is extremely important. What that means is that this clock counts down on average every 10 seconds, but on one trial it might be 2 seconds, the next trial it might be 21 seconds, the next trial it might be 13 seconds, then 7 seconds, but on average it's going to go down every 10 seconds. So on average rewards become available on this target three times more quickly than they become available on this target, but there's a lot of noise, a lot of stochastic
random noise here, and in order to estimate the rates you've got to integrate across that noise over time, okay?

Now when a reward becomes available, when the clock counts down to zero, and the reward's there it stays there, it hangs out right there on the target, until the monkey comes and collects it. And that's very important because it means that it's logical for him to collect occasionally on the lean target. So this one that's counting down rapidly, you can call that the rich target, the one that's counting down less rapidly we can call that the lean target, and you might say well why would he ever go to the lean target when the chances are always higher that he's going to get rewarded on the rich target? And the answer is that these probabilities are cumulative, so after you've gone to the rich one several times this guy up here has a very high chance of being rewarded, in fact it'll have a higher chance eventually than the red one will because the probabilities have been accumulating there. So it pays off economically; you get more water, you get more juice, for the return on your investment if you include this guy in your plan and you go out and check him out occasionally. Okay?

So you can imagine yourself sitting here doing this, and you're just sitting here like the monkey and you're going to the red one and the green one. Most trials you don't get rewarded, but you pick up a reward once every third trial or so on average, and your job is to figure out which one is the rich one. That's called the exploration problem in foraging theory. But then you also, once you figure it out, you want to exploit your gain. So it's the exploitation-exploration problem here. And it turns out that matching—when animals match—it's an optimal solution to that problem, okay, which Herrnstein figured out thirty or forty years ago.

So this is—I don't—it's hard to have sort of question-and-answer interaction. This is a time when I would stop and ask you, but is this reasonably clear here? Okay, all right, I see some heads nodding which is a good sign. All right.

Now, so the monkey is matching if his response ratio equals the reward ratio. So in this example where we've got ten seconds and thirty seconds he's matching if he makes 75 percent of his choices to the red one and 25 percent of his choices to the green one.

Now here's the final trick that we play. We have frequent unsignaled changes in the reward ratio, so the monkey's cruising along, he's got the world by the tail, he's judged that this one's three times more valuable than this one, and then suddenly the world changes. And we might reverse them, okay, or we might make them fifty-fifty, or we might make them 6-to-1, something like that, and so the monkey's—and people, we've done this on people also—they've got to be careful because the world changes. And this is typical of the world you and I live in, right? I mean the world changes on you—things happen, so to speak. So the animal's got to watch for these unsignaled changes in the reward ratio. All right.
Data on Valuation in Monkeys

Now this is data, these are real behavioral data that are collected over about eight hundred trials, this is one of these sessions. And I'm going to step through this slide fairly slowly because this again is another critical slide. What we're plotting here is the monkey's cumulative choices toward the green target against his cumulative choices toward the red target, and we've got eight hundred trials' worth of choices here, and the monkey's choices are shown by this brown line. And I'm going to unpack that brown line for you in a moment, or this yellowish brown line. The purple lines show you when we changed the world on the animal, and I'll unpack that for you in a moment.

First of all the brown line. By following this brown line you can actually know exactly what each of the eight hundred choices was. So if the monkey only chose green, if he just chose green time after time after time after time, this brown line would come right out along this axis. If the monkey only chose red time after time after time the brown line would go out along this axis. But he's switching back and forth, so the brown line traces out a trajectory through this space, right? And so every little rightward hitch means he chose green, and every little upward hitch means he chose red. So here he goes red, green, red, red, green, red, red, green, green, green, red, and so on. And here's he's making more red choices than green, here he's making more green choices than red, and that slope flattens out, okay?

Now these purple lines show you where we changed the game on the animal. So this first epoch of about eighty trials here he has a 1:1 ratio, he has an equal likelihood of getting rewarded for the two, okay, so the slope of this thing is 1, and you can see that this brown line is following the purple line nicely. Now right here there's an unannounced change and the rewards go 3:1 in favor of green. And you can see that very quickly this monkey starts making more green choices, and this brown line starts heading out to the right. At this point we go 3:1 in favor of red, and again he makes a change and the brown line starts heading more upward than rightward. And here we go back to 1-to-1, and there we have radical shift, 1-to-6, and here we have 6-to-1, and this brown line is nicely tracing the purple line which means simply that the animal's matching. This shows you that we've successfully trained this animal to do what Herrnstein said they would do to get an optimal solution to this exploration-exploitation problem, which is to match the ratio of their responses to the ratio of the rewards that they're experiencing. And remember, he's doing this with no cues to the fact that the world has changed, he's just got to figure out from his choices and his success or failure at getting rewarded, okay? All right, so the monkey's matching.

Now here's something extremely important. In the theory part of this talk, we are going to ask, What computation is the animal doing? What's the little computation going on in the monkey's mind to assess the value? And we can pick up a very important clue already. And the important clue is this: see how rapidly the behavior changes at the inflection points? It's as though this animal's extremely sensitive to
the change in the reward rates right here, even though this is stochastic and variable, and he changes his behavior almost as quickly as the actual reward conditions change. Now this one's a little more slowly, right, this is like a little motorboat spinning on its axis in a harbor, and this is more like a ship turning around this corner, but mostly these shifts are very, very quick, these inflection points are very quick. Now what that means is that the computation of value has to be local in time. If the animal were estimating over this entire period here, trying to get his estimate of the likelihood of getting a reward, he would not change this quickly, he'd keep cruising past this inflection point and he would only change very slowly out here, okay? So this animal in order to compute value must be paying attention to the most recent trials that he's experienced. Now he can't be paying attention just to the last trial, or else he'd be a slave to what happened on the last trial. He would never be able to estimate the probabilities, so he's got to estimate the probabilities integrated over a certain number of trials or not too many or else he wouldn't be able to change quickly and he'd lose rewards, he wouldn't be sensitive to the changing of the world. So that's an intuition that I'm trying to give you about this calculation, that it's local in time, that he's assessing something like the last few trials. And we're going to put quantitative description on that; we can really quantify that and put numbers on it, but that's a key intuition about this computation. Okay.

A Computer Model of Valuation

So up 'til now we've asked, How do we measure value rigorously at the behavioral level? And we've seen that following Herrnstein we can train monkeys to perform an ocular-motor matching task, and the monkey's valuation of the two targets is directly indicated by the way he apportions choices between the two alternatives. Now the next little thing is theory. Can we formally describe how value is computing within the brain? And, that is, can we build a model? And I've already given you now a key piece of insight that whatever model we build is probably going to be estimating value based on what has happened in the last handful of trials, okay.

Now here's the model that we've actually built, and this model we build and we implement it on a digital computer, okay, and it's a simple model of matching behavior, and what we're going to do is put this model together on the computer and then we're going to feed the computer the same kind of history that we fed the monkey and we're going to ask the computer to do the matching task. So the computer now is going to make decisions, we're going to feed it two choices, we're going to say red or green, computer, and the green's going to say well red. Okay? And we're going to reward the computer or not reward the computer according to the same algorithm that we've used for the monkeys, we're going to change the world on the computer just as we have changed it for the monkeys, and we're going to make a little model here of the computer's decision process, the way it computes value, we're going to make this explicit and mathematical, the way that it computes value, and ultimately we're going to see does the statistics of the
computer's choices match the statistics of the monkey's choices? And if we can reproduce the monkey's choices on the computer we have a good sense that we're getting our hands on the reality, the internal reality, that's going on inside this animal, and that of course is our goal here, to figure out what it is in the monkey's brain, how is the animal computing value, okay?

Now here's the model and it's very simple. It looks more complicated than it is. So imagine the computer sitting here making these choices, red, red, green, red, green, green, green, red, and at any point in time we can look back over our shoulder and see the previous fifteen trials or twenty trials or thirty trials of history, and the history is encoded in these ones and zeroes here. So a one means that one trial ago he selected red and got rewarded, so when there's a one here it means he got rewarded. A zero means that two trials ago he selected red and failed to get rewarded. Now these three blanks mean that on those three trials he chose green, so we go down here and we see he chose green and got rewarded, chose green and got rewarded, chose green and got rewarded, so time goes from left to right, it means we went green, green, red, red, green, green, red, red, and zeroes and ones show whether he got rewarded. So we have two streams of history here, we have a stream of history on the red target and a stream of history on the green target, and what we're proposing is that the animal and our model integrates this reward history with what we call a leaky integrator, that means that he computes his income—how much luck I've had on red and how much luck I've had on green—and he discounts this the further it goes back into the past.

Now that's just a physical statement of the intuition that I showed you that the monkey has to be integrating locally, okay? So the further back something goes in time the more he tends to forget about it and says it's irrelevant to what I'm doing now, I want to pay attention to what's happened recently. And $\tau$ describes many trials back the animal's looking, okay? And in our model $\tau$'s a free parameter, so when the computer's doing this and we're simulating all of this on the computer we can vary $\tau$ around, okay, and see how the computer performs as we vary $\tau$, and we're going to do that in just a moment.

So we're computing the income we got on red, and income just means, you know, these ones or the ones that are really going to count integrated by this sort of thing here, and we've got some measure now discounted in time of our income on red. We've got some measure discounted in time of our income on green. And we simply divide the red income by the total income and that shows the fractional value of red. Now if we had green in the numerator then we would have the fractional value of green. And the red is just one minus the green; they're directly related to each other. And this is what we call the fractional value, and it simply says what's the relative success, what's the relative income I've accrued on green versus red, or buying Dell versus HP, right, what's the relative success that I've had integrated over some short amount of time? And then whatever this fraction turns out to be we just say that's the probability with which the computer's going to
choose red, so we're postulating that's the probability with which the monkey's
going to choose red. And then once we have the probability, like it might be 0.7, so
if he's had good luck on red recently this fractional value might be 0.7, so that's
pretty high, 0.5 would be random, it means I don't know which one it's going to go,
and we set the probability equal to 0.7, and then we just flip a weighted coin that's
0.7 heads, 0.3 tails, and we flip the coin and that's the computer's choice. So then
we can do hundreds of thousands of experiments on this computer and when we
do this we actually see that the computer's behavior mimics the monkey's very
beautifully for a particular tau of eight trials, okay?

Now remember tau's our free parameter, and it says how far into the past are we
looking in order to make our judgments of income, and the answer is that we get a
beautiful match of behavior when tau equals eight, eight trials. And that comports
with our intuition about the monkeys, right, that they had to be doing this sort of
thing locally. So this just shows you that we can reproduce that behavior very
beautifully with a computer. And what this shows you is a systematic evaluation of
tau. So what we're doing here is showing you the harvesting efficiency. Of all the
rewards that become available, how efficient is the computer at harvesting these
rewards, so this is harvesting efficiency as a function of tau. So remember that's a
free parameter; this governs how far back into the past we're looking to judge
value, and you can see the intuition that I tried to give to you earlier, which is that if
you're looking way far back in the past, 250 trials back into past, your efficiency is
very low, because you're missing those turns. The world is changing on you and
you're not changing appropriately because you're averaging over a long period of
time, so your efficiency goes down. If you're only looking one or two trials back
your efficiency goes down because you're a slave to what happened on the last
trial. And where the computer is optimal is right here with a tau of about eight trials,
and it turns out that those two blue dots show you exactly where the data lie from
the two monkeys that we've trained on this task. Okay? And this is amazing, right?
The two monkeys have found this optimal place, okay, that the computer tells us
optimal is seven to eight trials ago, and that's exactly what the monkeys are doing.
And what's even more amazing here is that the monkeys are approaching the
optimal efficiency that the computer achieves. Now remember, these monkeys are
like you and me, okay, they're working but they get distracted, they don't get
distracted by the Web or something like that, but there are noises in the hallway
and they get distracted, you know, their leg itches and they get distracted, toward
the end of the day they're not very thirsty anymore and the juice doesn't matter so
much anymore and they get distracted, but nevertheless their harvesting efficiency
is very close to what our best computer model can get to, okay?

**Physiology of Value Computation**

Now this is a bit of a long-winded way of saying to you that I believe we've gotten
this value thing under control. We can implement this on a computer, we can
reproduce the animals' behavior, the animals' time window that they're looking over
appears to be almost exactly what the computer's time window that the computer
is looking over. So we posed this question for theory, we said, Can we formally describe how value is computed within the brain? And what we found is that under our conditions the value of past rewards is computed within a relatively short time window, weighted roughly exponentially, so there's that exponential decay, with a time constant of about seven to eight trials into the past. So now we actually have a description of the computation that's going on in the monkey's head, okay. Now this is a formal modeling mathematical description, but what we really want to know now is how does this get implemented in the brain? And that of course is a physiological question, that's what we neurobiologists ultimately are all about, what are the neural circuits within the brain that actually implement the computation?

All right, so I'm going to show you a taste of the physiology that we've done. But first of all let's go back to our model and just remember now that the key parameter in this model is fractional value, okay? This is what we're now postulating is the internal variable. Remember I told you that as a sensory physiologist you stand on the sensory stimulus. As a motor physiologist you can stand on the movement that the system puts out, but when you're looking at these internal cognitive variables that we're postulating where do you stand? And where we're going to stand right now is on fractional value because we know that this kind of calculation that yields fractional value can model the animal's performance extremely well. So this is our postulated internal variable, and we can go through as the monkey performs the matching task and we can calculate fractional value on every single trial that the monkey performs because he, too, has a history, and we can just apply these filters, we know the right tau now, it's about eight trials, we know the right tau, and we can apply these filters, and we can calculate this putative internal variable on every trial. And the question is, Do neurons in the monkey's brain seem to code this putative internal variable? And I wouldn't be up here if it didn't, okay? I'd be giving another talk.

Okay, so let me tell you a little bit about the macaque brain. This is the lateral view of the hemisphere, this is the front of the brain, this is the back of the brain. There are a lot of things we know. This is the visual cortex that Nancy was talking about back here. There are three areas that are high-level suspects for us to begin recording from, and these areas are high-level suspects because we know that they're involved in the high-level planning of eye movements, and they are the frontal eye fields up here in the frontal lobe, the lateral intraparietal area in the parietal lobe that I'm going to actually show you data from, and an area down here in the midbrain called the superior colliculus. And we have only recorded from LIP at this point, and I'll show you some data from LIP, but ultimately we're going to record from these other areas as well.

This is a coronal section through the monkey brain; it's a slice like this, and this is LIP buried in the sulcus right here, and there's one on each side of the brain, and I'll tell you a little bit more about that in a moment. This is just to remind you that if we look at the cortex blown up and stained for cell bodies, every little purple dot here is a cell body, this is the top of the cortex, this is where the gray matter meets
the white matter, and the cortex is a laminated structure and it's made up of hundreds of thousands of cells under any square millimeter of cortex, and the physiologists' stock and trade is to get these microelectrodes into the cortex. These microelectrodes are etched metal. The tip of the electrode cannot be seen with the bare eye, you have to look under a microscope. It's insulated down to within ten microns of the tip, and if you get this bare metal tip up close enough to a cortical neuron you can record the action potentials from single cortical neurons and study them one neuron at a time. This is what Nancy Kanwisher referred to as the gold standard for electrophysiology, really look at the action potential traffic of individual neurons. Now these electrodes don't hurt when they're in the brain, there are thousands of humans running around with these electrodes in their brain right now, as Gerry Fischbach told you yesterday about this patient with Parkinson's disease, they have these electrodes in for deep brain stimulation for therapeutic purposes, and they don't hurt because there's no pain receptors in the brain. You can do surgery on conscious human brains, you can take a knife and slice the cortex. You wouldn't want to do that, but you can do it and the patient won't say that hurts, they might say hey, I can't see anymore, what happened? But they're not going to say that hurts, okay, so it doesn't hurt. All right.

Now one other thing to tell you about LIP, LIP has been implicated in the spatial control of attention, and also eye movements as I've suggested to you. And one thing you need to know, because it's critical for what I'm about to show you, is that LIP on the left side of the brain codes the right half of space, and LIP on the right side of the brain codes the left half of space, so they're going to be operating in tandem with each other, sort of push-pull, left half of space versus right half of space. So Leo, my graduate student, gets his microelectrode into LIP, we know which LIP we're on so we know in this particular experiment we're on the left side of the brain, the electrode's on the left side of the brain, so we know that this LIP is coding the right half of space, which is shown by this little yellow egg yolk here, and we locate that and then we have the monkey perform the matching task. And one of these targets is in the part of space that this LIP cell cares about, and the other target is on the opposite half of space, so it's in the other LIP, but we're only recording from one of these guys at a time.

So the monkey's playing the matching game, and he's got two choices. He can move his eyes to the target that's in LIP's response field, okay, in the half of space it cares about, or it can move its eyes to the other target that's out of the response field. There's only two choices, right, because of the way we've set this thing up he could go into the response field or he can go out of the response field. So this is critically important, notice now the visual situation is the same here, red target to the left, green target to the right, although that flips on some of the trials, but in this particular situation the visual environment is the same, and within each of these conditions the motor output is the same. Here the eyes go right, here the eyes go left, okay? We've only got two conditions. But within all of those conditions now fractional value is varying, right? So sometimes he's going to choose this green target and because of his recent history, which we can calculate, right, we've got
our model now, we can calculate fractional value, and sometimes he's going to choose this one saying, "Oh boy, oh boy, I've got a good shot at getting a reward here," and sometimes he's going to choose this one thinking this is the lean target, but I need to go check it out every once in a while, and I don't have such a good shot at it, okay? So fractional value is varying even though the motor act is staying the same. Same deal here, he looks out sometimes and fractional value is skewing all over the place, okay? But we've got motor controlled, we've got sensory controlled, and the question is do the neurons track fractional value? And I'm going to show you some neural activity now, and this just shows you—remember, our plot here, fixation point comes on, monkey looks at the fixation point, and then these two targets come on, and the critical period is right here, after the two targets come on and this one- to two-second delay period occurs before he makes his eye movement, and he's valuing these two targets and he's trying to decide which one am I going to go to, and the question is, What does the neuron do during that interval when he's trying to decide?

And now I'm showing you what one LIP neuron does. This is activity, this is the neuron's activity measured with that microelectrode and it's plotted in spikes per second, so this is action potentials per second, as a function of time. This is the time when those two targets first come on, then we have this delay period, and zero over here is the time when the monkey actually makes the eye movement. Here he's going into the response field, and you can see there's this big burst of activity when the two targets come on, and then we settle down to a firing rate of around thirty to forty spikes per second until the eye movement gets made. Now the trick here is that he's gone to the right, but what we've done I've segregated out all the trials where he has a high fractional value, this is the top third of the trials with the highest fractional values where he's saying all right, I'm going there and I have a good shot at getting rewarded.

Now here is the activity on the lowest third of fractional values. This is where he makes the same eye movement, but he says I don't know, I don't have a very good chance here, and you can see the activity is lower. And then there's an intermediate third, and in the intermediate third the activity's actually intermediate throughout the trial, okay. So this is one condition where he chooses the target inside the response field. Now the other condition is where he chooses the target outside the response field, and when he goes outside the response field, now remember we're recording from this neuron and he's choosing the other one, and for high fractional values of this red target he's saying all right, I'm going out and I've got a good shot at getting rewarded, we have very low activity. When he's going out but he has a poor chance of getting rewarded, we have a higher level of activity, and so on intermediate. So this neuron's activity is nicely modulated by the fractional value. And we can take a bunch of neurons like this and average them together, and the picture cleans up nicely. So you can see that here we got a lot of activity when the monkey's choosing the target in the response field, as we would expect. We've got low activity when he's choosing outside the response field. And
this activity titrates out nicely by value. So the blue is 0 to 20, 20 to 40, 40 to 60, 60 to 80, 80 to 100. Okay?

So the bottom line here is that in this very first exploration what are the neural circuits within the brain that implement the computation, the bottom line here is that fractional value is represented in LIP, and the effects are often as large as those of the eye movement itself. Now there's one important thing for you to look at here, and that's dynamics. What's interesting, one of the things that's very interesting here is that time zero, remember time zero is when the two targets come on, and for the first 200 or so milliseconds of this response there is no effective value. All these curves are tracking together and value only hits LIP at this point here, two or three hundred milliseconds into the response. Now that's interesting, right, because that means that value is probably not calculated in LIP. Remember fractional value is integrated over the last seven or eight trials. By definition value has to be persist over trials, but there's nothing persisting right here. There is no value signal present in LIP when those two targets first come on, there's nothing persisting. What that means to us is that fractional value is, probably the original calculation is done somewhere else in the brain, and then it's getting downloaded to LIP on every trial. And one of the 60,000-dollar question is, Where is that? So the dynamics imply that the original computation of value is not performed in LIP itself.

**Future Research**

So the things we want to know in the future, and I told you we’re just beginning to study, the things we want to know in the future is: Where and how is that color-specific representation of value computed? So remember color is the key to value here; it’s the red target or the green target that have high values, so wherever it’s being computed it’s got to be color tagged. And then the value gets computed and presumably downloaded into LIP, and we want to know how does that color-specific representation become transformed in the spatial representation in LIP?

So with just the last couple of minutes here I want to return, take up a gauntlet that Richard threw down yesterday. Richard Axel, if you'll remember, talked to us about this odor responses, and the fact that when you present a particular odor to an insect you get activity at multiple locations in the glomerular map and in the mushroom body. And different odors will give rise to different patterns of activity, so the code for individual odors is not a matter of one neuron, one odor, but there's a distributed code, a distributed network that's very complicated, and the question that Richard raised was, Who's inside the brain reading that code? How do you look at a pattern of neural activity that's complex and across many structures and actually make a decision about what olfactant is actually out there in the world? And this is something just by asking that question that way, who's reading the code, it's the fallacy of the homunculus; it's like there's a little person, a little man inside the animal who's reading out the code. And somehow it's not a little man inside there that's doing that but the brain itself is doing it. And Richard said that
the ghostbusters would come today and try to decide for you, or for us, what it is or who it is that's reading out the code.

Now I don't have an answer to this question, but I have a way of thinking about it that I like better. If you really think about it, how do we know if a Drosophila can actually distinguish between two olfactants? Well you can only know that if there's a behavioral test, right? If you can devise a test or devise some natural behavior for the animal where the animal does one thing under olfactant A and he does another thing under olfactant B. In other words, the final common pathways that ultimately reveal to us the animal's perceptual ability is his muscles, right, it's what he does, it's where he goes. In our animals ultimately our revelation of value, this internal representation of value, is the animal's patterns of eye movements from one trial to the other. Now none of us think[s] that cognition really happens in muscles, okay, but there are areas of the brain that we know control motor systems, so I've already told you that these areas, LIP, frontal eye fields, and superior colliculus, we know on other grounds are involved in the high-level control of eye movements. And so to me it makes the most sense thinking these are the areas of the brain that have to program up the next movement, prepare it, they have to select the movement and program the movement, and that whole process of selecting the movement depends on reading out those codes about sensory information and about all these internal variables. So I personally think that we will find more and more in the coming decades that much of what we think of as high-level cognition is really sorted out in what we have traditionally thought of as premotor areas, okay? And I don't know exactly how that's done, what the algorithms are, but I suspect that the answers are going to lie in these kinds of areas.

So that's a progress report where we are to date. I think we're just at the edge of—those of you who are interested in psychology and economy will say there's a whole slew of questions here you can ask, you know, What about utility? Have you thought about the animal's utility, how utility changes with motivation? This is going to be a very exciting area of study, I think, and again, David, in five years maybe we can come back and have another look at it.

Thank you very much.

Question and Answer

Okay, so David gives permission for one question. There's a man at the microphone here.

Man: It seems that in this room we here have opened a tremendous can of worms, maybe not equaled since the first splitting of the atom, if I'm not exaggerating. If we're not careful it may be followed by a Manhattan Project, but it might be in the business school or political science or psychology. I think I've heard on [the] news that fMRI is being used for advertising, may be used by political groups. So do you
think this is a real danger now? And do you think that perhaps it's time for the scientists, before it gets out of hand, to speak up on controlling this technology?

William Newsome: So that's a very reasonable question, and certainly I think that all of neuroscience more and more will have impacts on society, and that there will certainly be ethical and societal issues that are going to be raised because of advances in neuroscience. I'm not very worried about the whole fMRI advertising thing. The one thing you should realize is that in my line of work the behavioral science precedes the physiological science, okay? It's the people working on behavior who have the insights. Herrnstein had this insight about value long before we got into this thing, and we're just using Herrnstein's insights to try to work out the mechanisms in the brain that underlie this sort of behavior. Similarly in color vision, back in the nineteenth century we knew all about trichromatic vision, and it was only in the middle of the twentieth century when physiology caught up. What I'm trying to say to you is that in terms of advertising the people on Madison Avenue know a helluva lot more than any scientist knows right now. They're the behavioral experts in this. Those marketing people, I mean all of politics these days and all of advertising is an exercise in human perception. And they know what appeals to humans and what makes humans lean this way or that way with their choices. And physiologists are just coming along afterwards and explaining, you know, why it is that this happens and where this comes from in the brain. Now can it ultimately make advertising more effective? Maybe so, I don't know, I don't know. But I don't see that as nearly as much of an ethical issue at this point as, for example, you know, all of the issues about neural transplants into human brains and things like that, you know, to what extent do we use human subjects inevitably as experimental guinea pigs versus the great therapeutic benefits that can come? And I see big ethical challenges in the area of understanding behavior. As soon as we start understanding behavior mechanistically then do we just turn behavior into a machine, and how does that affect our legal system? If my brain just made me do it, if all my choices I make because my brain made me do it, how can I be held legally responsible? But this is not an unprecedented choice, right? We've dealt with diminished capacity and we've dealt with things like this in jurisprudence for decades and centuries now. So I don't see this as fundamentally new. There will be issues that are raised, but at this moment I don't see anything terribly pressing. I mean I'm not getting ready to go and outfit all of your brains with electrodes so I can stimulate you and control your thoughts. Okay.

David Cohen: Thanks very much, Bill.

We're going to take a 15-minute break. We are running behind so we'll hold it to 15. I've just been asked to inform you that the organizers and speakers have put together an online bibliography and reference guide for the symposium. And at some point on the screen we'll give you the Web address.