Your Mind on Modeling & Active Inference, with Noor Sajid

0:00:02.1 Beth Fisher: Welcome back to Minds Matter, a podcast sponsored by the Monash Center for Consciousness and Contemplative Studies. I'm Beth.

0:00:08.6 Ava Ma De Sousa: And I'm Ava. And on Minds Matter, we explore research from neuroscience and psychology while talking through our own personal experiences.

0:00:17.7 Beth Fisher: And this week on the podcast, I spoke to Noor Sajid about her research on computational modeling. Noor uses the Active inference framework, one of the specific computational modeling frameworks, in her research. And she spoke to us a bit about that this week.

0:00:35.5 Ava Ma De Sousa: If you've been listening to our podcast for some other episodes, you might know that we typically just go into the speakers just introducing themselves. But I am not familiar as much as Beth is with this type of modeling specifically. And I think modeling and cognitive modeling can be a tricky concept in general to most people. Maybe you're thinking modeling as in like Bella Hadid, that's obviously not what we're talking about.

[laughter]

0:01:01.5 Ava Ma De Sousa: Before we jump in, I just wanted to clarify and ask Beth, who knows a little bit more, what actually is modeling in psychology and neuroscience? What does it do for us and how is it different than Bella Hadid?

0:01:13.9 Beth Fisher: [laughter] All good questions, and yeah, I just also wanna second what Ava says and if you listen to this and you don't understand everything, that's totally okay. I actually don't expect many people to listen to this for the first time and grasp all the concepts, but I think if you come away with some better understanding of some of the elements of computational modeling then you've done a great job. [chuckle] Computational modeling is how we can simulate and study complex systems, but already we have another word that it's... Wait, what's a complex system? A complex system is something that has many different components that interact with one another. A complex system could be the earth's climate, and that's something we could model. We could model social networks, kind of, we've spoken about social networks before, you can model the dynamics of those. You can model down to the level of a cell, the dynamics of a cell.

0:02:07.7 Beth Fisher: But probably what we're most interested in is you can also model the human brain. And as for what are we actually modeling? Is this telling us what's happening, in the neurons? What are we actually doing? In the Active inference framework, we are modeling something called a generative model and we're saying that this generative model is what the brain creates in order to make decisions on what it's gonna do out in the world. This is saying, this is what the brain is computationally doing. This is the equations that the brain is using to work out probabilities and make decisions. There are theories that go along with how we think that's implemented into the brain, what neurons we think are firing when this is doing these kind of equations. There's also theories about what the dopamine is doing and the different brain chemicals are doing during that, but they're more the theories associated with it that hasn't been proven so much yet. What we're gonna talk about is the computations we think the brain are doing. Is that clear?

0:03:13.9 Ava Ma De Sousa: Yes. Follow-up question. To be clear, as we go through and listen to this episode when Noor's talking about the model, is she talking about something that she actually thinks is happening in the brain? Are there regions of the brain that are involved and that she's talking about when she talks... She'll talk about the model breaking, for example? Is that something actually breaking within the brain because she does mention lesions, cuts in the brain, or is it really on that level that is more computational where the implementation doesn't necessarily matter as much?

0:03:50.8 Beth Fisher: Yeah, another that... Yeah, that's a really good question. And I think so, and Noor also mentions this, but the models that we're using at the moment also are really highly abstracted. We might say, oh, this is what we think is happening. But it's on a very highly abstracted level. We need more work to know exactly what's happening on exactly the levels on the brain and what regions and everything these processes are occurring. When she mentions that she's talking about lesions, we do something in the model that we think represents what a lesion is doing. We don't yet have the data to show that that's what it's doing, but we say, okay, we think that's what it's doing. And you can do this with other sort of things you might wanna model. You might wanna model someone who has depression and what you would do, you would think about, okay, well what are the characteristics of depression?

0:04:42.8 Beth Fisher: And then you would modify something within the model that you think would influence the behavior of someone with depression. So that could be maybe you think they have a different prior belief, they have a different belief than someone without depression. You might think they have a slower learning rate for some information than people without depression. These are all the kind of assumptions that we need to make. And then ideally we can, you know, make all these models and then also gather more human data and kind of get them to converge. And then also get neuroimaging data to see how these processes are actually implemented in the brain.

0:05:17.5 Ava Ma De Sousa: Basically when we model, we're kind of like trying to put the processes that we think are happening in the brain for a certain action to arise or someone to just do something into math, right?

0:05:32.9 Beth Fisher: Yeah, and 'cause the other thing is how are Ava and I sitting here having this conversation? How are we able to do all these actions? How have we made it in the world this far? All those kind of things and making those decisions. And on some level you might think, oh, that sounds trivial, that's just what we're programmed to do. And of course, we can do all this and do all that, but then if you think about it, yeah, but how do we actually do that? One of the things is, you know, we can understand what cause and effects are and all those things, but how is the brain representing that and modeling that so we can make the best decisions?

0:06:05.4 Ava Ma De Sousa: I think that's also maybe one of the tricky parts of this episode and Active inference and these big models in general, is that a lot of the times we focus on very specific problems. We focus on how do biases influence your political decision-making or something. But here the model is really how your brain works all the time. The reason that it's so abstract is that it's also trying to give an intensely general case that fits almost everything. And I think that's also why the language is so abstract. As you go through it, maybe you pick your favorite kind of problem, one that Noor will bring up is a problem involving what you wanna choose to eat at a restaurant. Or you can choose any type of problem that just involves you acting on the world, and think about the ways that she's talking about that in terms of that concrete problem.

0:06:54.8 Beth Fisher: Yeah, and one of the... I think the simple ways of explaining our generative model, it's a model of how do the causes that I can't say generate the consequences I can see? And it's, yeah, how does the brain work that out? To help you guys out a bit, some of the terms Noor will use we'll just explain. So one of the things that she mentions quite often is a prior. And you can just think a prior is something you have a belief about, and this is what you have at the current point in time. A belief you might have about anything. I'll have a prior about... I'm talking to Ava right now, what Ava is going to do. You have priors about all these things.

0:07:32.6 Ava Ma De Sousa: The reason that it's called a prior is because it's a belief before the time that we're examining an action is about to happen. So for example, Beth might come into this situation with me and she has... Maybe she has a prior that I tend to be late, but if I text her and I say I'm gonna be 20 minutes early then she's gonna have to integrate that new information into now her kind of model of me, just the way that she thinks about me, and that prior, then the next time that we meet, that prior might shift because of what she learned in this new interaction with us. And that depending on the time frame, a prior can also shift into a posterior is kind of the beliefs that you have at any given moment, but it's kind of about when you're looking at the action, and I'll let Beth define what a posterior is as well.

0:08:23.4 Beth Fisher: Yeah. Then the posterior is a new belief you have after you've seen a new observation. I'll have my prior, I'll get some information and then I'll get the posterior, which is my updated belief from my prior. Yeah, I have a strong prior that Ava is usually late, [laughter] I'll get some data about Ava being early, then I would get the posterior, which would be my updated belief about Ava being late or early.

0:08:57.8 Ava Ma De Sousa: And then the model is kind of all the stuff that happens in between that also determines how much she's gonna weigh or how much she's gonna take into account the fact that I was early this one time. It doesn't make sense for her to be, oh, she's definitely gonna be early all the time now, because that would just be erasing everything else that she knew before, there's kind of some sweet spots in the way that she can integrate that information.

[music]

0:09:29.2 Noor Sajid: Hi, I'm Noor Sajid. I'm currently a PhD student at the Wellcome Center for Human Neuroimaging and I am working with Karl Friston, he's famous for his ideas on the free-energy principle, and that's predominantly what I work on. And essentially what the free-energy principle is stipulating or it's saying that we as humans or biological agents are trying to minimize our surprise about the world. And my research is focused on trying to use that principle to try and understand how we can understand healthy behavior, so this types of things that you and I are doing in the world, but also when there are some sort of dysfunction. The dysfunction would be when there is some sort of perturbation in the internal system. What that essentially means is that the brain is broken in some way, and I'm trying to understand how the brokenness results in some change in behavior. So that's the main focus at the moment, which has been quite fun.

0:10:23.8 Beth Fisher: The free-energy principle is associated with this theory of Active inference, and I think this is something also that people are probably hearing more and more about recently. Could you explain what Active inference actually is, and how does that relate to the brain, how does that relate to our behavior and how can we use that in the research setting?

0:10:42.5 Noor Sajid: That's a tough question.

[laughter]

0:10:44.7 Noor Sajid: Simplifying Active inference.

[laughter]

0:10:47.0 Noor Sajid: I guess the way we consider it is that, we're trying to understand intelligence or some sort of intelligent behavior, and Active inference is a theory for that. It's that two description levels, so normative and descriptive. So I'm just gonna talk through the normative level. So the normative level is just a description of the best case scenario of what you should be doing, and it states that we as agents of the world have some sort of model, so when I'm interacting with the world, I have some abstraction that I'm embodying internally that represents the types of things that I'm being exposed to. For example, in this current given moment, my internal model is thinking about all the words that I'm going to be spilling out, but also making quick inferences about the types of things that you're saying. So for example, when you ask me to explain, I'm thinking internally, okay, so the explanation and then trying to figure out what to do. Under Active inference that means that I'm trying to minimize my surprise about the types of things that you're saying, but at the same time, I'm trying to also act in the world in a way that allows me to minimise my uncertainty. So it's sort of this spiel of I'm perceiving the world so that I know it best, and I'm also acting in a world that allows me to then pre-empt exactly what's going to happen in the future.

0:12:03.0 Beth Fisher: How can we then use that? So do we use this on a mathematical level, do we collect data, how can we use it and test that theory?

0:12:12.0 Noor Sajid: So you can use it at multiple different levels, and that's sort of what I've been working on doing at the PhD at the moment. So you can, the first instances you can do simulations. So you can use it as a process theory where you have some way of instantiating that normative account that tells you exactly what that internal or abstracted model should look like and exactly what the surprise or definition and the approximations that you want to bring into play should look like, and that those simulations give you an idea of the types of behavior that you would have if you were to get a human subject or some sort of biological agent to interact with the world. At a second level, what you can think about is you can have some sort of data that you've collected based on some experimental paradigm. And then what you're interested in is understanding where that data came from. So you would find a model and then you would invert the data to try and understand exactly what sort of hypothesis led to that data. And we did some work relating to subjects doing some word repetition paradigm, where you take that data and try and understand the sort of underlying mechanisms that are allowing for that particular data to be there.

0:13:24.7 Noor Sajid: And so, to make it a little bit more concrete, if you've got two agents that are interacting, in this case you and I, you could say that we have an environment where we are creating this spill-over of words as we're talking through, and that could be the data. And then in these Active inference models, you can take this data that we actually are seeing or observing at the moment and collecting from the environment, and then we are essentially inviting it, so we're trying to understand what sorts of states or hypotheses have led to that data at hand. And this is particularly useful because in a given experimental paradigm, you might have sort of a priority, particular hypothesis as to what a subject might be thinking about when they're trying to... Well, when they're creating that data, so to be able to invite it and understand exactly what the process looked like, it means it'll be useful in terms of quantifying changes over certain paradigms, and that's what I've been focused on, exactly trying to understand from a quantitative assessment what that data inversion looks like.

0:14:30.3 Beth Fisher: If you can explain a bit about the word repetition task that you used?

0:14:35.1 Noor Sajid: Yeah, that sounds good. So word repetition is a simple paradigm where you expose the subject to a particular word, so for example, read, and then they have to instantly repeat it. So that this from a language production and perception perspective, it's essentially a very simple formulation of both. So you're perceiving the word and then instantly producing it and under an Active inference formulation, it gives a very nice way of saying what is the word or the actual hypothesis of what I'm hearing. The read, the past tense of read, or am I hearing the word red, the color red? So you're making inferences, quick inferences about what that read is, and then you're instantly repeating it. So that paradigm has been used in trying to understand aphasia. So aphasia is a language disorder, and what I'm interested in is aphasia of stroke. So you have some sort of internal perturbation or lesion, and when that's impacting critical language areas in the brain, then I'm trying to understand exactly what's going wrong using that repetition paradigm. It's interesting though, 'cause when you look at word repetition from a behavioral perspective, it becomes very convoluted actually mapping it back to these abstract models like Active inference, where you have to discretise the types of behaviors of the experiment or the subject has actually been observing, themselves observing or the experiment's been observing.

0:16:00.3 Noor Sajid: So essentially what that means is that in the simple task where you have a healthy subject replaying the world instantly after they've heard it, there is a three-step epoch, and epoch is just the time steps you have. So you start off with the experiment is saying, "Can you repeat X?" and then the subject instantly repeating it and then getting some sort of positive affirmation post that. Whereas when you have some sort of deficit, functional deficit pertaining to language, then that sort of interaction becomes a lot more convoluted in the sense, subject should be asked repeatedly to repeat the word, they might stutter, they might repeat the wrong word, but then repeat it correctly moments after. So it's sort of making the same models be able to simulate or evaluate behavior both at a healthy level, and also at a sort of, I guess more interesting from a quantitative perspective, but very difficult where you have these disorders and people have much, I guess, different behavioral trajectories, which has been interesting.

0:17:04.2 Beth Fisher: And so you mentioned that this could happen with stroke patients where they have trouble repeating the word. So models like this, is there a way that they can help us understand the process in order that we can then trade it? Is that one of the benefits of this approach?

0:17:22.6 Noor Sajid: Again, that's a really big question. [chuckle] So I think at a very abstract level, you can use these models to understand what is going wrong, and the types of recovery mechanisms that could arise that would result in functional recovery. So you would have resistance to behavior loss that we see in subjects, but to make very concrete predictions or hypotheses about what needs to be probed. For example, in some sort of deep brain simulation analysis, to actually induce recovery patterns or get the behavior to come back is sort of an open-ended question. So at the moment, the models I'm working on are specifically within this context, are really high level, they give you an interpretation of the broken process, they give you a way of quantitatively assessing differences between health or control subjects compared to someone who has had some sort of brain perturbation or stroke in this particular instance, but to relate it back to very empirical, concrete hypothesis, I think is a sort of a long run agenda of mine, but definitely not there at the moment. But it does give you a mechanism of trying to understand how you can induce this types of lesions, for example, in our word repetition paradigm, when we simulate these models, we're trying to think about the neurological language models.

0:18:43.6 Noor Sajid: So the neurological language model is essentially stating that there are a set of neuronal areas that are implicated or propagating information when we are doing some sort of language task, in my instance the word repetition task. And it states that these areas are the important ones, so when we sort of simulate our model or define it, we're thinking about those areas and the types of processing that they're doing. So for example, this order to re-interpretation, and then propagating it onto some sort of representation about those auditory images, and then the actual movement of being able to perform that word or being able to say it, and then the phonological understanding and the actual articulation of that word. In our models we are replicating that and then we use computation lesions, so essentially where it is breaking some sort of connection with our model and then seeing how set behavior or the recovery mechanism would break.

0:19:43.5 Beth Fisher: I think previously, many of the researchers we've had on have done more brain imaging and things like this, so I guess it's probably interesting to people, well, what are the benefits of using computational modeling as an approach to study things like stroke, or language processing rather than putting someone in a scanner? Obviously we still need to do that, but one of the questions is, well, what can we gain from computational modeling that we can't from those previous approaches, what does it add and what can we find?

0:20:11.5 Noor Sajid: So I think there's always an additive effect. I wouldn't say that one is better than the other. So in my research I'm also using neuroimaging data that's been collected from both healthy subjects and stroke patients who've had language disorders. Those studies, the neuroimaging studies give us a very quantitative and experimental understanding of exactly what might be going wrong, but it doesn't tell us the mechanism or a process level of understanding of exactly what is breaking, exactly where the perturbation is happening, exactly how the information propagation is changing. Whereas in these computation models, you can actually control very systematically what you break, how you break it, and then evaluate the changes. So for example, in one of our studies, we looked at functional recovery mechanisms using the word repetition paradigm again. And with that we broke different parts of the model one by one to try and see exactly what was the requirement to completely break the system.

0:21:20.4 Noor Sajid: And it's interesting, when you go back to neuroimaging data, sometimes you'll have one focal lesion and functional recovery. Sorry. There is a behavioral deficit, so a massive behavioral deficit, whereas sometimes you'll have really large lesions and you won't have any behavioral deficit. So some of the work that we've been doing on the computation side is trying to understand what are the sort of key instances, even when it's in critical areas, what is changing that might be causing these differences that we wouldn't necessarily expect. So for example, in one of our models we looked at how you could have one lesion which would lead to some sort of behavioral deficit, but if you introduce another lesion, so it's called a paradoxical lesion, where you would then result in actually having a reversal of the functional deficit that you actually saw in the first place.

0:22:11.0 Noor Sajid: So it's called Sprague effect. We sort of replicated that phenomena and it gives us a very low level understanding of the type of evoke potential or the excitatory and inhibitory balance shift that you would need in order to instantiate this recovery pattern or behavioral, a reversal of behavioral deficit. Which is super interesting 'cause when you're neuroimaging you can only look at the system as it is. With these models, you can actually probe and investigate what's happening. And I guess at the second level what's really interesting is that if you are getting really good at modeling these phenomena and making it very realistic, then you can have digital models of subjects both like healthy subjects but also some of the folks who've had some sort of, I guess traumatic brain injury or maybe cancer or something where that there's been this change or perturbation in their internal system.

0:23:03.5 Noor Sajid: And then you can mimic the sort of things that would happen if you probe this or if you probe that. And that might start giving you an understanding at a very high level what could result in, I guess some sort of functional recovery in some ways. But again, that's like the long run goal and we're definitely not there at the moment.

0:23:22.9 Beth Fisher: So just then you mentioned an example of, so someone has one brain lesion, is that correct? And then they develop a second brain lesion, but that actually repairs what the first one had damaged. Is that right?

0:23:36.2 Noor Sajid: Yes.

0:23:36.7 Beth Fisher: Would you care to explain a bit about that?

0:23:38.2 Noor Sajid: So the effect is that you have a paradoxical lesion. So the idea, 'cause normally when you have two lesions, they're actually going to be worse than the first lesion. But in this instance, you are changing something internally in the system when you introduce the second lesion. So in our analysis we give an interpretation that is changing the excitatory and inhibitory balance. So you start off with introducing one computation lesion, which completely disconnects pathway between how information is propagated from one level of the model to the other. And that just means that there is no learning happening or there is sort of a rigidness in the model that we can't get past.

0:24:21.6 Noor Sajid: When you introduce the second lesion, what you're allowing for is learning to re-happen because there is more uncertainty in the way our connections are formed. So there is more way for the model to actually update and we qualify that using the change in how the model updates are happening. So by model updates I just mean how the structure of the model is changing over time. So when you're exposing the model to data that you wouldn't have had. Sorry, exposing the model to data that it's being exposed to post the second lesion is able to actually incorporate that a lot more quickly. And that changes that balance that I was talking about before, that you wouldn't have necessarily gotten if you hadn't introduced that second lesion. So it makes the model slightly more flexible post that second lesion that it wasn't to beforehand.

0:25:14.9 Beth Fisher: That's so cool. And do you think that that... So that's what's happening in the model. Do you think that that's... I mean, I understand that all these questions could be way further down the line, but do you think maybe that is what could be happening in the brain when this happens as well?

0:25:32.5 Noor Sajid: At a very superficial level, yes.

0:25:34.7 Beth Fisher: Yes.

0:25:36.0 Noor Sajid: I don't think I can give a more concrete answer. I think from my perspective, if we can understand how paradoxical lesions happen at a very refined level. So the work that I've done has been very high level and it doesn't really relate back to the neurophysiology in a more concrete way. But if we can start doing that, then it gives us a really exciting avenue to try and see what is happening when you do have these functional recoveries that you see in subjects with very large lesions, 'cause that's saying that there is some sort of learning or plasticity that's being induced as a consequence of these additional lesions that wouldn't have been there had you just had this one critical lesion.

[music]

0:26:19.0 Ava Ma De Sousa: Alright, so Beth, I had a question. I had a hard time following the idea of the two lesions and what happens when there's one lesion and then it gets cured with a second lesion or a second cut to the brain.

0:26:38.3 Beth Fisher: This I guess also goes... Steps out of the modeling world for minute. What happens is you have brain damage on the right side of the brain, and this causes left visual neglect. What left visual neglect is, is that you can't pay attention to things on the left hemisphere or the left side of what you see basically, but then what happens is then you get another lesion on the left side of the brain, so this is a second tumor now, and then all of a sudden you can pay attention and see the left hemisphere again.

0:27:15.8 Ava Ma De Sousa: And you all probably know this, but the left side of your brain is responsible for the right side of your body.

0:27:20.9 Beth Fisher: 'Cause I had a blood clot on the right side of my brain, and I was paralysed on the left side of my body, so I should know that.

0:27:29.0 Ava Ma De Sousa: Fun fact.

[laughter]

0:27:29.9 Ava Ma De Sousa: I feel that's a good one to remember, yeah. So the left... So If you have a lesion on the left side of your brain, it will influence and it's in the motor cortex or something or something that controls your body movements, it will influence the right side of your body and Beth has experience with this.

0:27:45.6 Beth Fisher: Yeah, again, it's okay, well then if I get a second lesion on my left side, how then does that repair the damage caused on the right side? When you get this second lesion, you modify the balance of these excitatory and inhibitory neurons, and this triggers kind of more plasticity in the brain, you change the balance of what neurons are being excited, and the neurons that are excitatory and inhibitory and then basically, it triggers a reversal of the deficit because it becomes more... There's more plasticity in that region now, and when we have increased plasticity in the brain, we can grow and reorganise the neurons, basically it's stuff that happens when we're learning and we're younger, the second lesion, because it changes this balance, kind of starts this process occurring again, if you have this process occurring they can learn the new connections and these kind of things and be like, okay, and work out how to attend to the left hemisphere.

0:28:48.9 Ava Ma De Sousa: Why doesn't the increased plasticity happen when there's only one lesion? 'Cause I've heard stories of someone losing something dramatic, literally losing a chunk of their brain, especially when they're younger and there's more plasticity and the brain can change more, and then other parts of the brain take over the functions that were lost. Why is it more likely to happen when there are two lesions?

0:29:10.6 Beth Fisher: I think it can happen when it's one lesion, it just depends where this lesion occurs. In the literature on this kind of stuff, there are examples where as Ava said people get one lesion and they're fine, people sometimes, 'cause I used to work more in imaging, people totally live normal lives and they come in for a brain scan and you see that parts of their brain are missing, which seems shocking but they live totally normal lives, which is... Yeah, I mean, the brain's amazing, you can just get one lesion and be fine, but this is just one of these examples when you get two and it changes, and this is an interesting case, it's like, how can one repair what another one has done?

0:29:58.1 Ava Ma De Sousa: Okay, I see. The reason that this is kind of a cool thing is that in some cases, you wouldn't have any repairs happening, but then this other lesion somewhere else, maybe that triggers some kind of plasticity and it has trickle-down effects to that first lesion.

0:30:15.2 Beth Fisher: Yeah. And then what Noor's work is doing, she's then modeling this process, and she's using Active inference to model this, but she's using the... So I mentioned that Active inference has a neuro process theory in how we think all these computations that are being carried out in the neurons, and she uses this to model the connectivity and firing rate patterns of the neural populations, and that's how in her model, she can show this plasticity difference with one lesion and two lesions, that's what her model is doing.

[music]

0:30:49.1 Beth Fisher: Could you explain how Active inference is different to reinforcement?

0:31:00.7 Noor Sajid: I think I say that I laughed because I think they've converged to a perspective where I think they're quite similar from an implementation perspective, so a lot of the stuff that I do is, I guess if I was to recast, Active inference would be a model-based Bayesian account of reinforcement learning, but at a very high level reinforcement learning is all about optimising the value of the state, so some expected return over some long-term period, in comparison, in Active inference we're optimising beliefs about states or beliefs about future states, and the types of things that we would exhibit or interact with in the future.

0:31:42.3 Noor Sajid: But I think it becomes a lot more nuanced when you start thinking about whether the algorithm, so for example, reinforcement learning or Active inference you're thinking about it in a model-based setting, then they're pretty much equivalent, especially this distinction between the reward function, so a lot of the time when you think about Active inference, you are thinking about a formulation where you don't have to stipulate a reward function, you are reinforcing behavior in a very different way, so you are essentially having a lesion that's self-evidencing, it's trying to minimize its surprise, so it's trying to do things, it's trying to do the sorts of things that would result in this minimisal of surprise or maximisation of the model evidence, and what that means is that I as an Active inference agent would want the data that I'm being exposed to or the data that I'm sampling actively from the world is matching my internal prediction of what the data should look like and where it's coming from, and I'm actively sampling the world in a way that just matches and reduces that surprise.

0:32:48.9 Noor Sajid: In comparison with model-based reinforcement learning, the story can also become very similar when you are thinking about how to learn that model. But there is a lot more flavors in the sense of how you do planning and that's where like the distinction really happens. So both model-based reinforcement learning and Active inference, which is inherently a model-based account 'cause you are thinking about some embodied abstraction that the agent has, but the difference is in the planning. So in Active inference, the planning comes from uncertainty minimization, which is essentially a way of sampling the world that allows you to trade off between both your extrinsic and intrinsic imperatives. Whereas when you take out the intrinsic imperative, you are left with reinforcement learning. So if you talk to folks in the field, they'll say reinforcement learning is a limiting case. But what's interesting I think in terms of like the current debate is that when you sort of go away from the certain embattled definition of what is reinforcement learning, so everything is in the service of maximising future reward, then you can start introducing these intrinsic imperatives that you would get within the Active inference planning objective, which is the epistemics or any sort of information gain that you are interested in about the world.

0:34:11.2 Noor Sajid: And then you can use that to say, actually they're pretty equivalent, but I think conceptually they're different in the planning objective, but from the types of models, from a model-based setting, they become very equivalent. But I think, so when I conceptualise it, I think reinforcement learning at a model level, if you're thinking about model-based Bayesian reinforcement learning at a model level, they are equivalent when you start thinking about partial observability. So in Active inference, we assume that there is some sort of hidden structure that's giving rise to these observations. So this is the embodied or the... Sorry, the abstracted embodiment of the world. If you then map that back to reinforcement learning, you can also have that, but you can remove the hidden causal structure. You can just have a process that's explicit in the sense that there is no hidden states.

0:35:04.1 Noor Sajid: Everything is known in the world, and you are transitioning and you are using that transition model to try and understand exactly what should be the next planning objective, or sorry, what should be the next action depending on some policy that you are learning. But then when it comes to the planning bit is where it becomes very interesting. And there's lots of literature on this in terms of like how do you balance like the extrinsic and the intrinsic merit imperatives and how do you sort of relate them back to, is it in the service of learning the model that the agent is equipped with, or is it actually to try and learn or interact with the world continuously in a meaningful manner even after learning the world? And in Active inference, the whole spiel is that it's always in the service of interacting with the world and making very refined decisions that are minimising your uncertainty about future observations, even if you have a really good understanding of the world.

0:36:02.4 Noor Sajid: Whereas in reinforcement learning sometimes it's all about just learning the world model and then you can... To remove these intrinsic imperatives and you can just start maximising the extrinsic or the the reward function. That's the end goal, right? So I think the field's at a very interesting turning point in terms of like, there is a convergence in terms of how people are thinking about these models, especially when you start scaling them up. So you are going beyond the simplified models that I was talking about in my word repetition paradigm, which are discreet in both space and time. So you are discretising the observations into different chunks and the hidden causes are also discreet in the sense that you have these conceptual or corpuses that you are introducing that relate back to the word repetition or the words in the word repetition paradigm.

0:36:55.5 Noor Sajid: Whereas when you start thinking about more continuous data, for example, a stream of images that the agent is exposed to or some sort of very high dimensional space, then practically both formulations I think are starting to converge with the same sort of issues of how do you think about the transitions of the world, as in how do you encode these or the exact dynamics, especially if they're changing across time? So you are dealing with data that's very stochastic, and for example, as a human or as an agent of the world, when I'm interacting in my world, I go from the house to university to the market, etcetera, and these are very different distributions or they're part of really large distribution. Whereas if I'm getting my little tiny agent to explore the world in the same way, getting it to go from like the house to university back to the market means that there might be massive changes in the environment dynamics that hadn't been pre-encoded, especially in these high dimensional settings where the agent might just be exposed to images. So it has to infer the context, it has to understand what the actual content means, and then make decisions based on that. So when you get into that sort of problem setting, then both algorithms are very equivalent in how they're dealing with like the implementation sort of details.

[music]

0:38:27.9 Ava Ma De Sousa: This particular framework called Active inference, but it is in some ways quite similar to another framework that we also use to figure out how humans and also animals make decisions and are able to live their lives, essentially make any decision and act on the world in any way. And so this framework called reinforcement learning is a framework which is really based on... It's actually kind of cool, I think, because it went from being a very psychological theory to then being used a lot in machine learning to kind of coming back in psychology. But... So if anyone knows a little bit of the history of learning in psychology, it all kind of started with Pavlov's, that's what is just called classical conditioning, you probably have heard the name Pavlov at least, and this type of conditioning is associated with Pavlov's dog, which was just him ringing a bell every time he was about to give his dog a plate of meat or his food, and then over time, there was an unconscious association that the dog made between the bell that he was ringing and getting ready to get his food.

0:39:34.7 Ava Ma De Sousa: So any time that Pavlov would then just ring his bell, his dog would start to salivate, and this is something that happens also in humans, you can think, if you've ever been in a class and you hear someone's phone alarm go off and it happens to be the same alarm that is the one that you use in the morning, you'll probably have a physiological reaction that is very unpleasant, and that's because you've just learned to associate that sound with, "Oh my God, I have to get out of bed and this sucks." After that kind of initial look into how humans learned, there was another step forward from classical conditioning, which was a little bit different from what Pavlov was saying, because in Pavlov's conception, there was really no kind of agent that was learning anything, it was just these unconscious associations, the agent really had...

0:40:22.7 Ava Ma De Sousa: The dog or the human in this case, had no kind of... Was taking no action in the world and it was just passively learning these associations, and [0:40:32.7] \_\_\_\_ learning comes with this other type of conditioning, which is called operant conditioning, and these are basically synonyms, but this is really just about rewards and threats in the environment, also with the animal example, we can think of the way that people typically train animals, a lot of the times now, people train their animals to do all these crazy tricks just with giving them rewards when they do a behavior that's very similar to what they want them to do, and then they slowly kind of scaffold up. In reinforcement learning there's also punishment, but I think that that is thought of a little bit less and also used less in general, but the basic idea is just that someone, an agent or an animal or a person will learn to do certain behaviors when they realize that their behavior, their action in the world, and this is why it's different than Pavlov, it's not passive, it's their acting in the world will lead to some kind of reward.

0:41:23.1 Ava Ma De Sousa: I think a great example of this is gambling, and the reason that gambling is addictive is that it has this irregular reward schedule, which just means that it's not every single time that you do something, you press that button that you're gonna get a reward, it's gonna be every 10 times or every 50 times, but when you get that reward, it's very intense and it makes you wanna continue to do that action, and that's kind of where reinforcement learning started, and then this idea of seeking out rewards in the environment and avoiding threats in the environment then was latched on to by people in computer science who are trying to get their computers to do more complicated things, and now it's kinda come back to psychology, and people have started using that as a framework for what the brain is actually doing, and there's some very cool research that shows that neurons are actually responding in similar ways where they fire more if they get a reward that they were not expecting, for example. Do you wanna say more about that, Beth?

0:42:17.5 Beth Fisher: Yeah, basically, as Ava mentioned, reinforcement learning, it's things about maximising long-term reward, it's about this reward function. Then I guess why is Active inference different? And I also wanna preface this to say I am not an expert on any of this, [chuckle] ext, if I say anything wrong, I totally accept that. [chuckle]

0:42:40.8 Ava Ma De Sousa: And if there are experts that are listening, please feel free to contact us and tell us that we are incorrect and we can always fix what was said and learn something new.

0:42:49.1 Beth Fisher: But in... So in Active inference, you don't have this reward function, it's not just about maximising a reward, it's about trying to fulfill these prior preferences, you select actions based on minimising the difference between your predicted and preferred outcomes. Where this gets interesting is in reducing uncertainty in information-seeking. What actions may I do to gain information to then get to the reward? We kind of understand this balance and what also Noor was speaking about between exploration and exploitation, you can be getting to your preferred outcomes through seeking information without directly just going to the reward. And that's kind of where it's different, why do I gain information to reduce uncertainty if it doesn't always necessarily relate to an instant reward? Okay, that answers that question.

[music]

0:43:55.8 Beth Fisher: I guess you've kind of already addressed this a bit, but could you explain the difference between exploration and exploitation, what that is and how does active inference address this problem?

0:44:11.1 Noor Sajid: Yeah, definitely. So one of the, I guess, the core issues within the reinforcement learning setting is how do you balance sort of exploration and exploitation? So the way I would just sort of situate that problem setting is that if you're going to a new restaurant... I'm sorry, if you're going to a restaurant that you've been to multiple times before, exploitation would be getting the same thing on the menu because you know exactly what you're gonna get, for example, if you like the Taifu Ramen or something. That's the one that you're gonna get every time. But then exploration would be that you haven't really...

0:45:26.5 Noor Sajid: You don't know the road or the sort of the outcomes if you tried something new, so you might go and be like, "Oh, I want to try, and maybe the bow or something," or, "I wanna try a completely different sort of meal, or maybe even go to a different restaurant," just so the exploration, exploitation trade-off is saying in order to maximize future return or some reward that I have, do I keep doing the same things that I know will give me that same level of reward, or do I try something different, in this case, like the bow or even going to a different restaurant that might give me maybe a much higher expected return in the future, but might also potentially give me something massively worse off? So it's just sort of balancing off between the two, and we as humans are constantly battling with that, if you're going to a Gelato place, do I get the same flavor over and over again, or do I try something new just because it might give me a higher expected return than I was anticipating?

0:45:45.9 Beth Fisher: So how do we know how much we should explore or exploit, and what happens if we get it wrong, so what happens if we just get stuck exploiting a certain option? Or is that a problem or is that okay, if it continues to give you some sort of reward, how do we know how to do that balance?

0:46:08.6 Noor Sajid: So in Active inference, and that's why I sort of honed in on the planning is different between reinforcement learning and Active inference. So in Active inference, the idea is that there is no trade-off between exploitation and exploration, 'cause it all comes under uncertainty minimisation, so there's intrinsic and extrinsic imperatives that I talked about, so extrinsic care is talking about exploiting or maximising some future return based on the observations or the environment you are inhabiting and the intrinsic is some sort of information gain. And here the information gain is over patterns that are seen, so it's information gain about the states. So for example, exploring things that are something that you find very interesting in the world and also intrinsic in the sense of novelty, where you are exploring parts of the world that are highly novel and help with understanding of the environment that you haven't been exposed to before, and so, under Active inference, the planning objective boils down to these three main things, the exploitation or the extrinsic imperatives plus the information gain over both the states of the world, but also the actual statistical contingencies about those environments that you are inhabiting.

0:47:33.3 Noor Sajid: So in terms of whether there is too much exploitation or whether there's too much exploration in the world, it entirely depends on how well you know the world, right? So for example, if I'm going around in my room over and over again, there's going to be no novelty, so I'm gonna stop doing that because every action that I take is a left right, up or down or lying down on the bed or playing some music, etcetera, is going to be very consistent in the way that I'm going to get some sort of novelty or information gain about the actual environment dynamics, whereas I might actually be getting some sort of state information gain if I play a new record in comparison to if I lay down, because those things have different sorts of state changes in my posteriors or the beliefs that I would have given some sort of new data that I have sampled, and in that instance, you would only be doing things that are exploratory in the service of actually minimising the uncertainty.

0:48:39.2 Noor Sajid: So there's no extra exploration and there is no unhelpful exploitation under the Active inference formulation, because it's all dependent on how well you know the model and the sort of beliefs that you have, if you have got the right sort of beliefs, the right sort of model and have some sort of preference, so prior preference over the types of outcomes that you would like to consider, which in the Active inference could be in some ways analogous to the maximisation of the reward function or exploitation, then there's a very nice balancing effect that you have, but there is, I guess, from an empirical or engineering perspective, you can introduce additional exploration by using hyper-priors over the information gain about how you're interacting with the world and what sort of information gain is relevant to you.

0:49:28.4 Noor Sajid: Priors might weight the exploration a little bit more than the exploitation, but practically that could also mean that you have some additional priors on how you even want to weight it and then you can be optimising all of that all together, again, in service of minimising your uncertainty or maximising the expected model evidence. And again, in that instance, there won't be an over-exploitation, over exploitation would be sub-optimal in the sense of the inferences that you're making given the world model from an objective perspective, but from a subjective perspective of the agent is very optimal, which is sort of a round-winded way of saying that it's all good.

0:50:10.9 Beth Fisher: Does that mean then if... Just say if people... So within their model, they're always doing the right balance of exploitation and exploration, but does that mean maybe if someone... For example, if someone has depression and they don't wanna go out much and they're doing more exploiting, does that then show up more through the belief or the way the model is set up, but they're still doing the right balance, is that how we could think about those kind of conditions through this?

0:50:42.8 Noor Sajid: So under the standard Active inference spiel, it would be that, over exploration could potentially... A consequence of these mis-priors that you have, so the priors are usually introduced into the model using precision formulations over a particular encoding of the environment dynamics. So for example, you could have precision, and here precision is how confident I am about certain things about the world, so for example, the door that I'm opening is actually opening, is... Or if I open the door and it doesn't open that those could be two... Sorry, that those could be two sorts of associations that I have learnt, and me doing the action of actually opening the door when I have very unconfident beliefs mean that I don't really believe that I'm the one opening the door, it could be something else doing that, so it's very unconfident belief over that.

0:51:37.4 Noor Sajid: So in that sense, when you introduce precision over these particular model parameters, you're essentially changing the confidence over them, so the sensory precision, which is what I was talking about, how the states that you are mapping back to the real world might not map appropriately, but it could also be that you don't know exactly what your actions are going to do in the world, so you can have very unconfident beliefs about that, so you might repeatedly do the same thing over and over again because you don't have appropriate understanding of the dynamics and how you are influencing those dynamics, so when you have those two issues at play in terms of the sensory precision, which is your hypothesis about what's happening and how it's changing the observed data and the transition precision to state transitions or how the world is evolving over time, when those are really imprecise or you have low confidence, then that actually maps back to when you're calculating your uncertainty or the true information gain that you have, right? Because when you're estimating your beliefs, because you have very unconfident priors, you're going to end up maybe doing the same thing over and over again, or over-weighting some things or you might have very flat priors, so everything is exactly the same.

0:53:00.6 Noor Sajid: So when you're selecting your next action or what to do, as in if you want to open the door or not, you will just keep repeatedly doing that because you're pretty ambivalent or you're exploratory in the sense of how you're interacting with the world. Another way that the model can potentially break is that you might not have any sort of preferences about what you actually want to exploit in the world, so for example, that could be completely broken, for example, I might just wanna sit in the room and not move at all, and that means that I have a completely imprecise or unconfident preference over the types of things that I would like to see myself doing, and in that sense, the extrinsic imperative from the planning objective part of Active inference would just mean that you end up treating all actions exactly the same, so then everything falls down on the exploration and priorities of the intrinsic in practice, and that's where you might just have a sort of separation between the types of actions that you can take.

0:54:04.6 Noor Sajid: But the Active inference, the standard spiel would be that the way you're planning is optimal, but the types of models that lead to those types of plans are going to be shifting with some optimal priors that mean that you have divergent behavior depending on the types of confidence you allow for different types of environment dynamics that you've encoded.

[music]

0:54:34.7 Ava Ma De Sousa: I know that this is wrong, but I wanna know why I'm wrong. The way that that is framed then where it's you want your model to just be as close to reality as possible, then in that case, wouldn't you just want to sit in your room all the time and never explore, because if you know that your room is going to be the same way that it always is, and if you always have your eyes closed, then you're good? That's what you're seeking. Is it just that because of the constraints of our world, that's just not how you can ever live because you have to survive and your biology demands that you have to go outside and eat food and you're gonna encounter predators or you're gonna have to go to work?

0:55:12.7 Beth Fisher: That's a great question, and that is something within this field called the Dark Room Problem, there's this big thing, well, if the brain is just trying to minimise this prediction arrow, why don't we just sit in the dark room and not get any prediction arrow? And actually, I was at... Yakob, my supervisor, gave a talk last night on this very topic, I feel I'm able to give a good answer, there's a few things as first of all, as, I mean, Ava, you kind of answered your own question, one of our needs is like, we get hungry and we need to eat, we wouldn't survive if we just sat in a dark room with our eyes closed because of these kinds of things, we need to go out and eat, maintain the same temperature, all these things, we need to fulfill those preferred outcomes. If you're sitting in a dark room and you have this prior preference for not being hungry, and then you're really, really hungry, you actually have this big, big difference in what you're getting compared to your preferred outcomes.

0:56:16.4 Ava Ma De Sousa: See, and also, yeah, we're not static because we're biological agents. I wouldn't... If I closed my eyes and I was in a dark room, I wouldn't continue to be in that state forever because I would start to get really hungry and uncomfortable. My environment in a sense would change because my body is changing.

0:56:35.4 Beth Fisher: Yeah. And not only are our bodies something that are constantly changing as the world, so the world's a really dynamic and can be a vol... Well no, can be... It is a volatile place. We also have to adapt to what's happening in the world around us. And that's some of Noor's work, which we didn't speak about so much, but I'll put her papers on our website, is about, okay, well when the dynamics of the environment are changing, so when there's more volatility, this means things are more unexpected than normal. Yeah, what do we do in terms of exploration, exploitation? Are we better off when the world is changing to go out and explore things more? Or are we better off just explaining our options? And this is one of the questions that a lot of researchers are looking at, and because one of the big things that has happened recently in terms of volatility is COVID, we had these ways of living that we were all doing, and then there was this massive thing that happened in the world, and we all had to... We were in a very volatile environment and we all had to change how we were engaging in the world. And yeah, so it's... You have to... You think about those instances and what... Yeah, what we need to do. And sitting in a dark room wouldn't have helped then either. [chuckle] Maybe it...

0:57:48.7 Ava Ma De Sousa: But so what do people do? Do they... Did people tend to explore or exploit more during...

0:57:54.6 Beth Fisher: I think this is also, it's a very individual thing in terms of the exploration exploitation difference? It can depend on... Yeah, the individual's preferences and things that... And I think when we had Kelsey on, we kind of spoke about this, about in terms of traveling and having these new kind of experiences and updating our self model. And some people have more tendency to do that than others.

0:58:17.9 Ava Ma De Sousa: That's so interesting because it's funny to hear about these very different ways of thinking about the brain and stuff. Because I'm in a social psych PhD program that is pretty heavily social, even though I'm in a, technically in two social neuro lab, we do a little bit more of this, but what I'm learning in class is very, very social psychology. And I feel there's just ways that our social psych concepts can really map on to these types of computations. But we haven't done it yet. And in social psych, there's a framework that's called regulatory focus, and it basically just talks about how different people have different preferences for avoiding... Or different motivational forces that lead them to be mostly focused on avoiding threats or mostly focused on gaining rewards. And that really influences like the way that they live their lives and that influences the way that they see the environment.

0:59:16.4 Ava Ma De Sousa: Because let's say you start at a new job and you have this so-called prevention orientation, which is you're worried about avoiding losses. You see a lot of threats. You're paying attention to the threats, and then your long-term goals become also about avoiding those threats. Whereas the reverse is true for someone who is more promotion focused or is more focused on rewards, who will then see all the opportunities they have to make friends and do cool projects. And it sounds like that is kind of, that could very easily be formalised through the Active inference framework. And what... Also going back to prior episodes where there's a mathy way to be looking at how much people prefer these different things. And I think it's also good to hear that in the Active inference framework, there's room for individual differences.

1:00:00.8 Beth Fisher: That's one of my favorite things about the Active inference framework is that we all have our own generative models and every generative model is performing at the right level, all operating under ideal Bayesian assumptions. The only thing that is different is, you know, our prior beliefs or some of the parameters of the model. And I think, so if they're different, then maybe your model's still operating at the right level, but then you might not be leading to the best outcomes in the world. Then I think that that's really hopeful because it's okay if someone has depression or anxiety or something is, you can just help work out, okay, well what priors or what parameters are not, you know, are not set up in the best way for you to function in the world, and how could we potentially help those rather than, oh no, there's something fundamentally broken in the way that your brain's computing things? Whereas this is no, your brain can do this. We just have to work out what, yeah, what parameters or beliefs or these things, parts of the model we need to help with.

[music]

1:01:29.4 Beth Fisher: So is there anything new you're working on or anything exciting you'd like to share?

1:01:34.7 Noor Sajid: So I've been working on lots of fun stuff. I guess one thing which goes back to what we were just discussing is the, so in, and that's why I kept on saying under the standard Active inference field, that you would have suboptimal models with the same sort of planning objective. Whereas some of the recent work that we've done has focused on keeping the model consistent. So you're actually not changing any of the priors, but you are changing the optimisation objective or the planning objective. And that actually leads to changes in the behavior that would otherwise manifest if you change the model priors. And the way we've done that is, so in Active inference when you are optimising your model, you're minimising surprisal, or surprising things, sorry, minimising surprise about the data at hand. And that comes from essentially minimising a divergence between two different types of things.

1:02:31.0 Noor Sajid: So your actual model and some approximate belief about what were the true hidden structure that gave rise to a particular data that you're being exposed to. So that gives you one way of measuring the surprise and optimising the agent's model. Another way to do that is actually sort of making that divergence a little bit more flexible. And that's what we've been looking at. When you introduce some flexibility in it, you allow for some fluctuations in the way you actually approximate those posterior beliefs. So the posterior beliefs are what would be the... What was the hypothesis that actually led to the data at hand. And when you make that flexible, you're allowing for different types of optimisation strategies to take place. And these optimisation strategies might mean that you might go from having a greedy optimisation or inference procedure to having a very sort of flexible or open-ended optimisation procedure.

1:03:35.2 Noor Sajid: And when you take a model that's being optimised under these flexible strategies, use that for planning, you can get these very different types of behaviors. And we show that within the scenario of a multi-arm bandit task, which is essentially that there's no transition dynamics. It's a one state, which means that at every time point the environment forgets exactly what happened at the time point before, but it has the same underlying distribution that's being sampled from over and over again. So you can use that to evaluate the types of things that I was talking about in terms of flexibility in the model not being a precondition to the differences in behavior, you can actually keep that model fixed and then change the planning objective to be a little bit more interesting. And I guess what's fun about this work is that the divergence that we are using to make these optimisations flexible is a general case of the standard divergence. So the KL divergence or the Kullback-Leibler divergence that you would use. And they're called the Rényi divergences, which I think are really fun. So I've been working on that a little bit and some other work as well.

1:04:45.0 Beth Fisher: And with this more flexible way, do you see outcomes in a more similar to data that you see? Is it more promising in terms in terms of this?

1:04:56.8 Noor Sajid: So from an empirical question, we haven't really taken it back to human data at the moment 'cause it's extremely difficult to design experiments where you can actually disintegrate where the behavioral differences might be coming from, as in are they coming from the changes, the priors or they're coming from the change in flexible optimisation objectives? So that's something that we are hoping to do hopefully during my post-doc, answer in a very simple way. And based on the experiments, we see that the changing of the optimisation objective has a very continuous scale that you are going from one end of the spectrum to another. And it's the same way that you would have when you're changing the priors.

1:05:35.7 Noor Sajid: So the behavior that can emerge in the two problem set-ups can be very consistent, but in our experiments there is no one-to-one mapping between that behavior. So we started with the hypothesis that it should be, if we were to believe, I guess, certain theorems, but it doesn't practically manifest when we're looking at it. So the next question is that when you start thinking about more complex systems or when you start going back to experimental data, how do you actually design the right sort of paradigms to measure that?

1:06:07.8 Beth Fisher: Is that something that you are thinking about, like what kind of paradigms you would... 'Cause I can't even begin to think about, yeah, what that would look like. [chuckle]

1:06:16.7 Noor Sajid: So I think the one-armed bandit, oh sorry, the two-armed bandit task, the one I was talking about would be a good setup, but you would have to give everyone a very explicit model so they have the same priors and then you would put up certain parts of the experiment setup. But I haven't really fleshed out, I can't say, for certain [chuckle], but hopefully in the next, once I finish the PhD, that's what we will focus on, how do these sort of more flexible optimisation strategies help with changes in behavior? Which is fun.

1:06:56.0 Beth Fisher: And do you think it's more likely that we are using these flexible optimisation strategies?

1:07:01.6 Noor Sajid: Again, I think it's an empirical question mostly because they have very explicit assumptions about the types of message passing schemes that you would have. So each of these flexible optimisation strategies have very explicit interpretations in information therapeutic terms. And what we are interested in is when you make those assumptions about, okay, so the optimisation space, we are going from a spectrum of infinity to negative infinity, for example, infinity would be relating back to the minimum description length. And if you start thinking about it in those terms, then that divergence or that distance actually has very explicit meaning for the types of messages and how they're being propagated within the neurodynamics that we're interested in. But again, that's something we haven't really fleshed out in terms of what that means empirically. Because it gives us hypothesis about how the flexible strategies could potentially relate back, but it doesn't really tell us whether there are differences, because all of these models, the process level models are very open-ended because you have to have someone then go in and completely evaluate what's going on.

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1:08:43.1 Ava Ma De Sousa: Thank you to Noor Sajid for joining us this episode. Our intro and outro music is Nobody Stayed For the DJ by Glassio. Our transition music is Back For More, also by Glassio. Minds Matter is mixed, edited and created by Beth Fisher. She's the Australian one, and me, Ava Ma de Sousa. We'll be back in two weeks with a brand new episode of Minds Matter. In the meantime, find all our episodes and show notes on mindsmatterpodcast.com.

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