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Symposium Part 1

Speakers List along Topics:

3:46 Tim Schneider

Presentation Topic: Active Inference for Robotic Manipulation

32:10 Tim Verbelen

Presentation Topic: Robots Modeling the World from Pixels using Deep Active Inference

1:01:10 Ben White

Presentation Topic: Artificial Empathy: Active Inference and Collective Intelligence

1:34:04 Noor Sajid

Presentation Topic: Learning agent preferences

2:04:13 Wen-Hua Chen

Presentation Topic: Dual Control for Exploitation and Exploration and its Applications in Robotic Autonomous Search

2:39:49 Roundtable with Wen-Hua Chen & Daniel Friedman

[session: "2nd Applied Active Inference Symposium on "Robotics" – 1st Session"]

[section: "'2022 ROBOTICS SYMPOSIUM INTRO' with Daniel Friedman and Bleu Knight"]

[sp: Friedman]

00:29 Welcome everyone to the 2nd Applied Active Inference Symposium, hosted by the Active Inference Institute. It is July 31st 2022. And this is the first session of the symposium.

[sp: Blue Knight]

00:48 The focus of the symposium will be robotics, and the presentations will be centered on that theme. If you have ideas for future symposium topics and want to participate in organizing, please reach out to us. For those of you watching live, please post questions in the chat and we will ask the presenters during the roundtable discussion.

The symposium will be recorded, transcribed, and archived for lasting access. We will make the playlist available for asynchronous participation. If you would like to participate in the transcription of the video please reach out to us at activeinference@gmail.com.

01:28 We will have five presenters followed by a roundtable discussion. The presenters in the first block are going to be **Tim Schneider**, presenting **"Active Inference for Robotic Manipulation,"** with coauthors [Boris Belousov, Georgia Chalvatzaki, Hany Abdulsamad, and Jan Peters]. And then next is **Tim Verbelen, a**nd he is presenting **"Robotics Modeling the World from Pixels using Deep Active Inference."**

02:23 And then next will be **Ben White** with **"Artificial Empathy: Active Inference and Collective Intelligence."** And he has coauthors Mark Miller and Daphne Damakas.

02:59 And after that, we will have a talk by **Noor Sajid "Learning agent preferences."** And then finally, we have **Wen-Hua Chen** with the talk called **"Dual Control for Exploitation and Exploration and its Applications in Robotic Autonomous Search."**

03:43 So with pleasure, I introduce Tim Schneider. Please take it away.

[section: "PRESENTATION TOPIC: 'Active Inference for Robotic Manipulation' with Tim Schneider"]

[sp: Tim Schneider]

03:50 Thanks a lot for the introduction. I'm quickly going to share my screen. I hope you can see that. So my name is Tim Schneider, and today I want to talk about our work on Active Inference for Robotic Manipulation. {So} I think we can all agree that manipulation is one of the central abilities that we need in our everyday life, {like} be it cooking, writing, or using tools; and you can obviously think of a variety of other tasks that also require dexterous manipulation. However, despite this significance of manipulation in our everyday life, robotic manipulation is still a largely unsolved topic.

04:44 And one of the main reasons for this is that usually in classic robotics, how we did it for years, we always assumed that everything is known - that we know where everything is, how everything behaves. But in unstructured environments, this is usually not the case. And so what we need is very adaptive policies that are able to react to changes in the environment and are robust to all kinds of perturbations. {So,} What my lab focuses on, or at least in part focuses on, is applying reinforcement learning to robotic manipulation. So, learn these skills instead of programming them by hand. However, this is also not super-straightforward in manipulation. And one of the central challenges here is to perform the exploration. So, in reinforcement learning, we always have to explore tasks before we can complete it.

[image: "Simulated tilt-table with blue and white background']

05:43 Like for example, here in this task, this robot has to move up this little ball into a target zone on this tilted table. And what we usually do, and what is done here, is that we just apply some random actions in the beginning and also throughout the entire optimization procedure.

And we hope that this will give us some useful insight into how the world actually behaves, and how we can create a high reward in these settings. But in manipulation, this is usually not the case. Because if we just apply random noise, we end up dropping the objects we are trying to manipulate, we end up maybe destroying even parts of the environment! So this approach is simply not feasible for interacting with the real world in manipulation.

[video: "Toddler experimenting with stackables"]

06:31   And if we look at how humans explore the world, we see a very different pictures. {So} This is a toddler that has obviously the task of building the highest possible tower out of these blocks. And what we can see is, that this toddler is not simply applying some random noisy actions. This kid has actually a fairly directed way of exploring, and has an idea of what is useful to learn, what might bring it forward. Or maybe, this is not as planned, but more of an intuition. But, certainly, this exploration is much smarter than what we are currently doing in reinforcement learning.

[image: "Industrial robot arm"]

07:10 And so to summarize this, exploration is a very challenging task in reinforcement learning for manipulation. Humans, if we take them as an example, explore very actively and in a very directed fashion. And the question that we want to ask in this work is, Can we do this with robots too? And so this is where we started looking into cognitive science and also came across Active Inference, mainly because it proposes a way or it proposes a theory of explaining curiosity in intelligent beings.

07:25 And the question was, whether we can transfer this {on} onto robots. So for completeness, I want to quickly go over the basics. So in Active Inference, we assume that every agent maintains some model of the world, which consists of observations '*o*,' hidden states '*x*' that the agent cannot observe, and some actions or policy '*pi*.' And the objective is to minimize surprise, which is the negative log likelihood of the marginal observation probability under the model of the agent. And the agent has two ways of doing this.

08:24   The first one is inference, understanding the causes of the observations it is making. This is done by applying variational inference to compute an upper bound of this objective, which is called variational free energy. And then we minimize this, which corresponds to finding a variational posterior for hidden states, given the observations we are currently making.

08:49 And the other avenue, which is what got us interested in the topic, is the selection of actions in order to minimize this free energy objective. So if we want to do this, we have to make sure that we plan ahead, so we have to take an expectation of future states we might encounter. given that we choose some form of action. And we take this expectation of this free energy term. And what we get out is fairly interesting; namely, we get this formulation here, which decomposes into an expected information gain term and an extrinsic term. And the way this expected information gain term works, or what it encourages, is to take *informative actions.* Because this term becomes maximum when we take an action which causes us to learn as much as possible about the current latent state of the world.

09:46 So for example, if you're in a very dark room, a very informative action would be to turn the light on. It's not immediately goal directed or anything, but it will at least tell you where you are, what your surroundings look like, and so on. And then the second term is this extrinsic term. And here the agent maintains a preference distribution over observations. This is a bit of an unorthodox thing for me as a reinforcement learning person - we usually simply define a reward. But here this extrinsic preference is defined in terms of this target observation distribution. But this is also exactly the point where we can inject a target behavior into the agent by basically saying, Okay, this agent should prefer to observe some specific observation.

10:39 Now, taking a step back and going to the reinforcement learning part of this talk again. The problem statement that we are looking at is a finite-horizon MDP, [Markov Decision Process,] which means that there are states, actions and rewards. We assume that these states fully encode the entire state of the environment; so there's no hidden states in the environment. And the objective of the agent is to maximize its expected return for one episode. And the challenge here is that the dynamics and the reward distribution - these two distributions here - are completely unknown. So the only way the agent has to figure those out, is to probe the environment with different actions, observe the outcomes, and then learn some kind of model out of this. Obviously, there are also other ways of doing this, this model doesn't have to be learned; but in our case, it will be learned.

[image: "Equation for P-sub-pi"]

11:45 Now, we can see reinforcement learning through the lens of Active Inference. I wrote down this MDP again, from the previous slide here.

The first thing we need is to define the internal model of the agent. And we do this in a way that we say - "Okay, there's two models the agent maintains, one is a model of the dynamics and one a model of the reward distribution. And both of them are modeled as Gaussian distributions, conditioned on neural networks. So these are neural networks, '*theta*' being the neural network parameters. And this introduces a latent state now into the environment, namely the neural network parameters. So what was '*x*' before in Active Inference is now here '*theta*', the only thing that the agent cannot directly observe, which is what are the optimal parameters that describe what is currently going on in the environment, what the agent is currently observing."

12:45 And the second thing we have to do is to, we have to make the agent desire high reward. And we do this here by making the reward part of the observation. So now it's observing the environment state and the reward. And then we are setting this desired distribution in a way that it prefers high rewards, namely, by setting it to the exponential of scaling factor *beta*, times the reward a time step *t*. And if we do this, we end up with the following planning objectives:

[image: "slide 'Obtain a weighted sum…'"]

13:20 So this is the expected free energy now, but everything put into its place. And so the planning objective of the agent is now, according to the expected free energy, to maximize *this* objective here, which consists (for one) of the extrinsic reward, which is just the sum of rewards the agent expects to encounter by taking some policy *pi*. And then there's also this intrinsic term again, which in this case here becomes the mutual information between the neural network parameters *theta*, and the observation the agent is making. So ideally, the agent wants to make observations that are both good in terms of reward, but also have a lot of information about what the ideal model parameters are going to be.

[image: "Algorithm 1"]

14:12 And now we can use this to forge an algorithm out of that. It works like this: {So} In every episode, we start by resetting the agent to some initial state. And then in every step, we have to solve this planning objective of selecting a sequence of actions that minimize the objective function I showed here in the previous slide. We execute this action; obtain a new state and reward; we store all of that in a replay buffer; and then after the entire episode is done, we use this data in the replay buffer to perform the inference step of learning our models and adapting them to the data we saw.

14:56 Now, the challenging part about this is to perform this optimization here.

And the first challenge here is already to compute this term, even for any given action. {So} Computing the expected reward for a given action has been done before in many works. And usually here Monte Carlo methods are used - estimating this expectation via Monte Carlo.

[image: "Approximating Mutual Information in Real Time"]

15:27 But this intrinsic term, which is the mutual information, is known to be fairly hard to compute. And so there have been a variety of methods proposed to compute or to approximate mutual information; many of them rely on variational inference or amortization. But the issue is that we would have to do variational inference over the model parameter *theta*, which is a fairly high dimensional vector. And also, we have to do this potentially thousands of times in real time, while we are optimizing this function here. And so this is simply too expensive to do anything fancy like that. So what we are left with is a nested Monte Carlo approximation. And "nested" because we have an expectation of a K-L [Kullback-Leibler] Divergence. This means we have an outer expectation and an inner expectation. And we apply Monte Carlo for both of them. And the good thing about this is, first of all, it's very fast, and it allows us to represent *P* of *theta* by a set of particles, because we now only need samples. So we can also just keep the samples and treat the entire model as an ensemble. But the disadvantage is that, we require quite a lot of samples of *theta* in order to get anything done here. Because we have this outer and inner loop, for every sample that we draw for this outer estimator here, for every sample of *theta*, we need to have n j samples of this inner estimator here, of *theta* again. And this means you can quickly calculate, if we take five samples on this outer estimator and five on the inner estimator, we already ended up with 30 samples of *theta*. So we have a quadratic growth in samples that we need in order to compute the samples, this neural information approximation.

17:38 And what is also important to note is that each of the samples is a full neural network that needs to be trained and maintained. So this is simply going to be very expensive, very quick. And so what we propose to do instead is something that is a bit illegal in terms of math, by at least it will lose us a lot of formal guarantees. And that is to use the same samples on the outer estimator, as we used in the inner estimator, vice versa. So to use in the inner estimator, the same samples of the outer estimator. That means we draw a bunch of samples once. And then we use all of the samples except the one, we just now use in the outer estimator to perform this in estimation. And again, as I said, we lose some form of guarantees, because what usually is assumed is that the samples are IID. This is not the case anymore, right now. But we found empirically that this actually improved sample efficiency a lot. So here you see a little comparison, we did on a randomly generated discrete probability distribution, where we could compute mutual information accurately. And here you see a plot of the error of the sample reusing estimator, the second one compared to the vanilla estimator that doesn't really use samples. And this is over the number of samples.

So the sample efficiency is actually much higher, even though we are losing these formal guarantees here. Now, this means we now know how to approximate or get at least some approximation of this objective, but what is still unclear is how do we actually maximize this objective, like what kind of optimization algorithm we are using? And the first thing we tried here was to simply use a vanilla cross entropy method. This is a fairly common choice in robotics to use this method because it's very robust and doesn't require gradients and anything and it's also considerably fast. It works in a way that you initialize some Gaussian parameters. So you always maintain this Gaussian distribution of your current action distribution. You initialize it to mean zero and one variance, then you sample a bunch of action trajectories from this distribution. For each of these, you evaluate the reward. And then you collect the n samples that have the highest reward. And for those you fit the parameters of the current Gaussian distribution you have over actions in order to gradually shift this distribution towards areas of F that have a high reward. And if you iterate this for a while, usually end up with a fairly, good plan. Now, the issue is that, applying this delivers fairly poor results. And the reason for this we quickly found is something that is called detachment, what has been called detachment in prior work, I should say, I don't think this is an established term yet. And the problem works a bit like this.

So consider you're in this completely reward free environment. The only thing that there is intrinsic reward, that leads you to explore this environment. And you start in the middle here of this maze and you can either go left or right. And in green is everything that is intrinsic reward.

So everything that is not explored has a lot of intrinsic reward left. And so the agent decides maybe to go for the left side first, it explores it for a while, but at some point decides that now the more immediate intrinsic reward is towards the right side, because this part has been explored now. So on the right side, it's easier to get intrinsic reward. So it might switch over to exploring the right side first. And remember, this is an episodic. So after a couple of steps, this agent always gets reset to the middle and has to do this over again. And so at some point, the right is maybe completely explored or whatever. And now we are in a bit of a tricky situation, because we again starting in the middle, but the entire right side is explored and the left side is so much explored, that in the immediate vicinity of the state, there is actually no intrinsic reward left.

And because many planners that worked well on high dimensional problems rely on very local optimization, we found that these planners are unable to find now a trajectory that leads all the way into this zone with high intrinsic reward on the left. And the reason simply being that in cross entropy method, in order to reach this zone, you would have to randomly sample a complete trajectory that goes all the way around this maze and ends up somewhere here in the middle, or like at least somewhere close to the border of the intrinsic reward here. And this is usually not happening. The solution for this, we found is to realize, first of all that the only reason there is no intrinsic reward left in this area here, is because we already explored it. So at some point in the past, we must have taken a trajectory that led us all the way around towards the border here and stopped somewhere here. And so what we can do is, we can simply remember all the past trajectories we took, and use those as an initialization for the cross entropy method to start off the planning from. So the way this looks like is that in the end, instead of simply returning the plan, we store the entire plan together with the current state and a memory buffer. And then when we plan for the next time, when we start the planning, we not only sample from this initial distribution, we also sample from this memory buffer, take into account all the previous plans we had and start optimizing those as well. And we found that this usually leads to behavior that is where we will be able to escape this area of low intrinsic reward. And that brings me to the experiments we did.

So this is a task we designed to be specifically hard to explore. So the task is as I said before, to move this ball into this target zone. The tricky thing is that first of all, the table is tilted. If the robot loses the ball, it ends up somewhere here on the bottom and it cannot be recovered anymore. So the robot has to wait for the end of the episode to continue exploring. And also the reward is completely sparse, meaning the reward is zero everywhere, except for if the ball is in this target zone. And this means that the robot has to explore this entire environment purely based on intrinsic reward and without any extrinsic signals in the beginning, until it discovered this reward for the first time. So if we apply like as I told you before, this classical technique and reinforcement learning of applying some random noise, we can see that the ball gets dropped immediately every time and even after like that 1000 episodes. You will soon see, we are not able to reach even 1/3 of this table. So here on the right is a histogram of positions, the ball has visited so far, and we are completely unable to leave the start of this table.

However, if we use our method, we can see that we actually explore this environment in a very systematic manner and achieve a very good state coverage, or at least poor position coverage. And our agent is quickly able to find this reward here and find a strategy that consistently pushes it into the right location. This is also reflected in a learning curve, is a comparison with a bunch of baseline methods re ran, one is pets, which is just a model based reinforcement learning algorithm. There's also suck and mpbo. And neither of these methods managed to find the reward in the given time. So we ramped it up a little bit, made this task a little bit harder. So what you see here, holes in this table. So now this becomes a nice day still no extrinsic reward in the lower area, and also up until here. So that means that again, based purely on intrinsic reward, the agent has to learn to maneuver this ball around the corners of this maze into the target location. And although it takes a bit longer to train here, obviously, because this task is much harder, it's also important to note, once the ball is inside of this hole is lost, and it cannot be recovered. So although this is much harder, and it takes a bit longer, you can see that our method is able to solve this problem and push the ball into the target location at the end. So this is a bit of a slower version of this policy. And you can see that it is actually fairly tricky to maneuver around these corners. There's a learning curve here. And surprisingly, the baselines did not manage to solve this task. But this expected since it's harder than the previous one. And finally, we also evaluate our system or our algorithm on the real system. So we built this actually in reality, and train it from scratch. So there's no transfer going on, no pre training and simulation or anything. And you can see here the behavior is similar, the agent starts exploring the environment more and more pushing the ball systematically around and ultimately discovering the reward on the top of the table, and then finding the consistent strategy of moving it up. There's a learning curve for this as well. But this brings me to my conclusion. So we presented an algorithm based on Active Inference that is able to solve very challenging sparse reward manipulations tasks.

And at the core lies this augmented cost function that is derived from the expected free energy. And this one, encourages the agent to perform very directed exploration while also maximizing report. And we demonstrate that this method works not only in simulation but also on a real system. And so to give you a bit of an outlook, what is very important to note is that if we compare to human haptic exploration, we humans rely very heavily on tactile sensing for all of this exploration, we have developed a variety of different strategies for actively perceiving using tactile sensing, for example, rubbing an object to figure out the texture, or what you can see soon in this video, like rubbing it with our full hand, in order to figure out the shape, can measure temperature, there's all kinds of stuff we can perceive actively from objects using tactile sensing. And tactile sensing is also something that is being actively researched in the robotics community, there have been a variety of new tactile sensors coming out lately.

29:17 One of them is the so called digit sensor. You can see it here. And it works in a way that it has a gel that deforms upon contact with something. There's a camera in the back and some LEDs. And if there's some contact, you can see the deformation of the gel in the camera, which is giving you some local tactile feedback. And it would be very interesting to see what we can achieve with Active Inference on using tactile sensors, although there is a variety of challenges that need to be solved. This is a high dimensional image. The contact dynamics are much more complicated, and there's a lot to consider. But this would be a very interesting avenue for future research.

30:02 And this also brings me to the end of my talk, I want to thank you a lot for your attention. I want to thank my collaborators as well, Boris, Georgia, Hany and Jan Peters. If you want, you can check out our paper here under this QR code. There is also a project page, which will soon contain an extended version of this paper that has been accepted to IROS. But I haven't uploaded it yet. So I will do this within the next one or two weeks. So if you're interested in more details, I recommend you to check this out. But again, it's not up yet. And there's my contact details in case you have any more questions. So if I got that correctly before we do the questions afterwards in the roundtable, is that correct?

[sp: Friedman]

30:52 Correct. Thank you very much, Tim. You may exit and re-enter the stream when we go to the roundtable. And there'll be just a few seconds of a break.

And then we will be going to the next talk, which is Tim Verbelen **“Robots modeling the world from pixels using deep Active Inference”**. So we'll be right back.

[editorNote: "2022 Robotics Symposium 1st Session ~ Part 2"]

[section: "PRESENTATION TOPIC: “Robots Modeling the World from Pixels Using Deep Active Inference' with Tim Verbelen"]

[sp: Friedman]

32:01 All right, here's Tim Verbelen talk: robots modeling the world from pixels using deep active inference.

[sp: Tim Verbelen]

32:11 Thank you for inviting me. So unfortunately, I could not make it live, but I recorded this talk for you. And I hope you'll find it interesting. I'm going to highlight, stretching out the picture what we work on. And put it short basically what we want to do is you do not have have robots that can model the world they live in from pixels. But basically we can extend it to any sensing modality using factory entrance. So why do we work with robots? Well, basically, we figured out that if we want to have something intelligent, enough to build something intelligent that's actually doing something relevant in the real world, then you need to do action, you need to interact with the world. You need some embodiment. And that's why we work with all kind of robots. We have manipulators that can scatter around, grouse objects and directed objects, you also have navigating robots that can drive around and fly around. So you might be wondering, why are you looking at both navigation and manipulation and everything there all over the world, there are labs that are dedicated on manipulation as a single domain and navigation as another domain.

And they're distinct problems. Well, the thing is that can be taken from another approach indicated from an active inference perspective, then it's basically the same thing, you're doing the same thing. And that's why we're trying to combine all kinds of robotic problems from this single scope, and see to what extent we can address it and solve them and to compare where are we compared to state of the art in the robotics, that's like our overall objective. So in the start out, talk a bit on sketch out, what is the general approach we're taking, and then some current results in both navigation manipulation and some of the work in progress that we're excited about and working on. So let's start off with what is active inference? I guess most of you will know already, but just to set the scene and grow for at least next 40 minutes, on the same page regarding location. And what do i mean that terminology so basically, active inference means to us, we have our agent or brain that just built a generative model of its environment, which we call the joint probability over outcomes. So action ‘a’ then some hidden states. So your agents is distinct from its environment that can interact with the environment by doing actions. It gets some observation, then I try to model with the hidden state, like how is this environments generating my observations, and can I model this to this mistakes, we use the single principle of optimizing this, thing by minimizing circle figurity which is like an upper bound on surprise or prediction error.

And importantly, not only you use this to model this instinct to build a model of the world, but you also use this to select the actions that you will hold, that will minimize your expected future. And looking at everything from a standard of minimizing your prediction error, not only for the past, but only for the future, this basically gives you a very powerful mechanism to start doing robotics. So math equations, that relates to this reality concept, to basically minimizing the big entails, having the complexity minimization. So you want to have the simplest model that explains your growth product. On the other hand, you also want to have an accurate description of how the world works. So you want to take your outcomes is basically means that you're having all the information that's out there in the world, you can actually have this Secret Invasion, that it's safe that you want your explanation as simple as possible, according to sphere. And this list view is basically the variational sphere, which is saying, I want to be able to reverse the model, like if I have some observations, I want to be able to infer what is the most likely states that could explain whatever happens to now, the scale of the game. And that if we look at the future, then of course, we don't know, outcomes that will come in the future. So now it's basically the same formulation you can have expectation also considers what might happens in the future. So what outcomes might I create and then your expected strategy becomes again two terms one is the instrumental value. It just says, how do I think the outcomes that I witness will actually realize what I expect to be, what I want to be like, it's realizing preferences.

And then in a reinforcement learning context, you might see this as a reward scenario, but rather, having it's coming from the environment. It's not more something that's intrinsic defines what you’re as an organism and then note the second term which is, “How do I think my beliefs will shift for what I think now that will happen versus what I think my state belief will be if I supposedly get these outcomes”? And you're basically searching for the observations that will gives me more information about what to do. So automatically you get this, on the one hand, goal of direct behavior. But on the other hand, your agent is also driven to find out development observations, find out information in this environment. But of course, we have a scallop deep, active inference flavor, where we basically want to learn this model, just by feeding a data, basically, we use these deep neural nets that are so called artificial intelligence nowadays, it's basically a function approximator, where you give it some data, and then you can can match any function with them. And we use these done to approximate the densities that were on the previous slides. So how does it go, you have observations or actions in this, with those two neural net, which then represents this approximate posterior, so this outputs mean SR deviations or precautions fusions, and they're like, your posterior distribution. So it looks like a bunch of multivariate functions. And this is then your state visitation, what's happening right now, given the observation that happened to now, then we have a new an additional neural nets, that then predicts the dynamics in this latent state. If I do these actions, how will my state go in the future, this outputs again, parameters of Gaussian institutions for example? And this allows you to plan in this latent state space, what will happen if I do this or that. And in order to train the model from each of the states, we can then have a decoder model that then tries to predict the observations that you expect to see from the state.

So the training mechanism is then minimizing the energy, which unveils here you have your accuracy minimization, so you minimize reconstruction error when it's safe and you minimize complexity, which basically boils down to this thing and the second slide, what I expect to happen, without observations, I want to have it as close as possible to what I expect has happened, given that I solved the observations. And by minimizing the scale divergence, we basically of course small to have very concise encoding that allows you to imagine what might happen at the same time emerging information coming from your outcomes, but not more than as necessary. So you don't want to necessarily model all the details in your pixels, for example, as long as you have enough information to predict sufficiently. So that’s like roughly the approach.

So now look at the some instances in robotics cases and we’ll start with **“NAVIGATION”.** So in this case we have roles but then with some additional sensors mounted them, so we can get all kinds of inputs, we drive him around this environment, makes it seem like a warehouse setup, where we trade these bubbles that have to predict, for example, from camera images, what will I see, if I do certain actions, and then after trading such neural nets, then this is the thing that we get.

So these are basically imagine its use from a viewpoint from a prominent site service lab environment. And now you can say, what do you think will happen these are actions. And this has been a thing that it starts imagining, and these are four different samples from this distribution. So you'll see at the beginning, they're all imagined the same thing. But as further you go, the more they disperse in the modelling all kinds of scenarios what spikes happen in the future. You can also see that even though the model is trained on long sequences, it doesn't really capture long term dependencies, or fairly accurate location information. Like, here if I turn it around, I’ll be facing the wall. But if I turn around on the other part the severe things will happen. I’m in the middle of the nowhere. Now, I’m at the edges, let’s say. So all has this inside the model that these all kind of scenarios that can happen. But because we conditioned these models on the action, we can also generate action conditions. And so we can say what will happen if I can go right, or left or go back or forth, what will to actually encode these dynamics inside this model. And this is training on data, from driving around and learning to predict what can happen. So, one of the things that we found out is actually by creating such a model, we can end up Perfect. That's pretty time to compare, or is your prediction what you think will happen to your posterior belief, but what's actually happened given your observation. And then what's the version between the two which is kind of notion of the base size of the model. And then if you put a new object like you've a stable header there and the robots drive over it, then this dynamics have never seen before, which is a huge spike and spike in the robots like, what's going on here. And in order to show that this is not measuring the difference in pixels, we also have this scenario where people are walking by robots, which also happens when you're recording the data. So this is the normal scenario. And then actually, the robots, it's something that didn't need to be supervised. So here you can see, it's more than learning pixel dynamics. Actually, depth is, this is the normal state versus this is a weird dynamics. And one of the nice things from using these virtual models is that you can actually put in any sensible, so we focus a lot on pixels, because that's also nice to visualize. And you can relate to how it looks like. But we can also give it like bigger lights, you can see the computer sweep and there's some ranging and here we have like a rainbow which is bit more expensive. Basically, the range axis like something, it just means is something just moving towards me or is going further from me. Also, we can then have their imaginations of the model, like, what's going to happen in this state space, you already saw the pixel but also relates like okay, this is how lighter scans will be, this is how radars will be, if I'm looking at the air, I see much more reflections in the radar image first, if it leaves the ale, it has only a few reflections.

So it actually catches all these dynamics from any of these modalities in this living space. So that's one of the strengths of this project. But as I told you, it has very narrow, like temporal definite, can predict for a few seconds, maybe one seconds, maybe two seconds, but then it becomes dispersed and blurry. So you cannot really use it for like long term planning. So we figured out, what do you need to do in order to use the system, but then, do something more relevant long term, and we figured out that what we need is go a little higher, and make like an hierarchical model that instead of predicting, the next sensory observation, it can, predicts, which state to expect, a bit further in the future. And the response in this, blue part is what you actually saw right now, but then the red parts are really combined some ideas from engineering from slab rock, what is the thing that you expect me, in the minutes or a few seconds there, and it's actually like, I'll do that at a certain location right now.

And in a few seconds, I'll be at a different location and this different location will there be more kind of observation and poses that I expect to be there. So if we implement such a model, it basically boils down to having on the one hand, this is extraction of the sensory inputs, which is what you saw before, and then together some representation of the post, if you turn around, keep track of it. So you know, where you're heading, and you have some sense of both integration. And then these two combined, then built a map, which is then becomes your model of the roles is done traversing this map, and then we get something like this. So we're here to begin to set up, so here we have the camera, now we have an encryption from the sensory inputs. Here we've the odometer which is very nice. You can see it go over the place. But then, by integrating both disrupt sense of where you are together, it's what do you think it looks like? And then combining, this force and you it's pretty much the same as what I visit before then, it's probably the segregation and emerge too, so then you see the lecture covers different nails in the lab, and it actually makes sense out of it. And then you can basically use this model to predictive like what this is looking like and you can use this to plan longer, longer term things.

So than we go to the more **"MANIPULATION"**. Kind of use cases, where we have like a robot arm and camera on the wrists or in actually getting information where it is focused to look at, you might think, like that, very different use case. But again, the way we approach it, it's an agent that can move around. And its main objective is to predict, what would I see if I move around, and then use that to figure out how this works? But of course, now it has much more degrees of freedom. But other than that, the concept says the same. Here we basically have the similar thing where basically learns other viewpoints from the information government. So first we give it back and it's straight. And then it legal all kind of businesses in the workspace, which figures out and it was trained on simple cases with some blocks in front of it, and simulation, then, if you start adding observations to the system, you can see how all the different poses are imagining, there was a yellow cylinder there. So in these viewpoints, I probably need to imagine the cylinder. And this way, you can start building the road and reconstructing the road from all viewpoints. So it's always predicting the future observations from information and dots. And the model is improving as information that then you can of course, also use a model to assess, which will be a new point that I haven't seen before. But if you meet some new information, and then basically what we do is, we use this energy term to then drive, what we found with them by just doing this mechanism in this case, we also give it like a preferred observation like the blue cube. The current observation doesn't looking at the space. I want to found it a bit actually, first goal goes all the way up because it's what it figures out. We'll give more information and then it will start zooming in scavenge for the preferred observation and they stay there. It was a really cool effect to see from just the principle that works right now goes up to have an overview. And then once it explored the workplace you can vary it in normal viewpoints. So this is again, imagination space of the robot arm wandering around, like you have in the navigation scheme, but now with robotic arm action speed.

So it's again the same principle, but we get similar results out of it. But then, of course, we were thinking, Okay, we need to throw a lot of training data, like different scenes or different objects added before it starts imagining these scenes. But if we look at how we learn, how the world works, how the world around us is, and then toddlers are actually looking at objects and manipulating them and looking at a single object of time. And that's how they learn. To me, this is the better way to learn in the manipulation scenario, how the world is working. So this then what we did, instead of having trajectories of random sees, we made the robot look at particular objects, and then predict other viewpoints but still on the same object, is always looking at the same location and predicting how will this thing look like from this side, and then basically get something very imagined for this particular object. This is how the dynamics are for this object. And then we take a similar model, but then we train it on a different object.

So now, instead of having a huge deep learning model that has to be learned about any object around, we can basically compress this into much smaller units. And then we instantiate a new instance, for every new object. We can give it notes or, can or a banana. And then you can start imagining how all these objects look like from other views. But then again, you can give it like a preferred view, and then all four, which will be a trajectory that brings you to the preferred view. And that's done. So I can see you, so then the top view is that I could target randomly, given the viewpoint and then figures out how to move in this space, just by imagining how this objects look like from different views, then I can also use this specified objects, because if we then have a random object, that they either had seen or never saw before, it can use all the models and vary like, which model is actually matching my prediction for what I'm seeing right now. And this then gives you like show me that object.

And you can see, you get for an initial view. It's already pretty printed set knowing what it is, but in some cases, you have a very ambiguous viewpoints, you cannot really distinguish the two objects, and then you can have another view. And that will then resolve the ambiguity. And that's exactly what we see here. So the agent will look for the most informative view. And then for the nominal objects, it reaches to 100% accuracy. And for this particular case, it's not 100% accurate. And why is that? Because there are objects that might be very related. So for example, it knows about spoons, and then you give it the fork, and it's like, it's like a spoon. So I'm not sure but these are the errors, it makes the visual accents, but actually, the dynamics of the object are very much matching an object I know before. And then if you query it, what would be the next view you would like to see? You typically want one with a low expected free energy. But if we ask it, what would be the view you don’t want to see than you get this kind of imaginations in the right most flow.

This particular view is very dark so I can’t really distinguish it from anything. The mystery bubble in the bottom right, this looks like a banana, so this is not the viewpoint I’ll choose to go next. But in practice you saw these objects are so distinct and a random agent is also good at just integrating information because the chances are low that you actually end up in this ambiguous viewpoint. In this scenario, it's equally well just randomly looking around but the more your objects become ambiguous, the more benefit you have from activity sampling particular viewpoints. So the same thing as using radar and camera from navigation. It's using tactile and visual information for inferring what this object is like to me as a robot. We have done that particular experience yet on tactile because it's also a bit more difficult to assimilate and it's on your mind to do these things. But it's very interesting route. And so finally, we can also do is look at the C. With different objects, and I say, I want to open the can. So I need to have the top view of the can. And normally, if you've this type of circular gray thing inside the gold image, the only thing you have to do is randomly search around, see something alike and then go to the target. But in our case, the system have this thing probably more related to the can rather than instead of the sugar box. So it’ll draw it’s attention to the can, and then also this is more like a top view, this is more like a side view, you can imagine like the thing it should the movement that should make to go to the top view. So this is the curriculum for those who just give it to you, it directs attention to the correct object, and immediately finds out the movement that should make to get that was similar. So that's really powerful system. And you can see this adding another layer on top, it's similar to the navigation where you really don't have an extraction of locations. Now you have like, okay, I can obstruction objects being somewhere spatially arranged, and infer where they are and how she moves in this space or to a patient. So then, through end it's something that we are actively and actually getting working on this, is basically, okay, we now have the system where we can build a model, where we can relate action to what is happening, but one of the difficult thing is still the further in time, you should plan, your potential of trajectories explodes. You cannot plan using all these fine grained actions.

So then we'll figure out these sensible actions or skills that you can use to explore. So one more thing, in order to avoid this explosion of options, is to amortize policy. So now, betrayal, again, a function that is done Amortizing policy that given the state gives you the action. But instead of using a reward in your lesson in reinforcement learning, you basically give it an objective that's more likely related to the expected to be energy. So in particular here we use what we call Latent Bayesian Surprise which was terminally invented to relate more to the oral community. But it is just like the information game on your expected states basically and then we actually found out to play these video games just purely from an intrinsic motivation. And also if it is compared to others, like terms that they add in the url’s to get this intrinsic right, reaction found the permitted was either bar are slightly better than others, and especially in cases where we add some noise in the States. So if the look observation are noisy, or ambiguous environment, it still wasn't it was more easy to outperform the others because noises likes very interesting. So we're done, noisy observations, although maybe they don't give you extra information.

So that was something interesting with math. And we are expanding them. Instead of having this is more an exploration policy. But now we're thinking more like, if we go to plan, maybe we don't have a few distinct options that make sense to explore. Like, can we find some elementary skills that are worthwhile to explore. So in this case, we have a robotic arm, and he'll be explore using this intrinsic drive for information gain. But then we give it 32 potential slots to learn policies or find out which ones are good trajectories that in total, allow me to explore the state space together. And then we ended up with like a manageable set of skills that we can then fine tune for particular tasks. And that's actually one of the things that we're working on right now. So that's my talk. Thank you for listening. I hope you enjoy it. Should you have any questions? You can always reach out via email or via Twitter. I hope to see you soon in the next edition. Thanks.

[sp: Friedman]

1:00:57 All right. That was Tim Verbelen's presentation **"Robots modeling the world from pixels using deep active inference".**

[editorNote: "2022 Robotics Symposium 1st Session ~ Part 3"]

[section: "PRESENTATION TOPIC: 'Artificial empathy, active inference and collective intelligence' with Ben White"]

[sp: Friedman]

1:01:06 The next presentation is going to be by Ben White, **"Artificial empathy, active inference and collective intelligence".**

[sp: Ben White]

1:01:10 My name is Ben White. I'm a first year PhD philosophy student at the University of Sussex. And I want to start by saying a really big thank you to the organizers for inviting me here today to share this research with you. It's a real pleasure to get to do this, even if it's in a pre recorded format. I want to say right now, at the outset that this is very much a collaborative and ongoing project. It's work that I've been doing with Mark Miller and Daphne, Demakus to make us and it's very closely related to the things that I do here at Sussex. So I'm interested in looking at the relationship between human wellbeing and material environments. I'm interested in things like ambient smart technology, social media, augmented and virtual reality, and affective computing, which is what I'm going to be talking about today. Because this is an active inference symposium, I'm going to afford myself the luxury of not going over the basics of the framework.

And instead, I'm going to jump straight in. And I'm going to tell a fairly broad stroke story about how we think active inference might be able to shake things up in affective computing.

So affective computing is a research program, which, aims to build computing devices, capable of interacting with human users on an emotional level by identifying, categorizing, and responding appropriately, to emotions in human users. And to give some examples, we have the paper in the top right from the MIT computing lab. And this project aims to put affective interfaces into cars, because any of us who drive know that there are certain emotional states we can sometimes find ourselves in, that probably hinder our decision making process, and that can have some pretty negative outcomes. And so this project was really geared towards increasing road safety by intervening in the emotional states of drivers, the two devices at the bottom, so the screen and camera in the bottom center, and the rectangular headed guy who's yellow, these are Gibeau, and woebot, respectively.

And these are therapeutic interventions that use facial recognition technology, emotion recognition technology, to learn about their users, and then make suggestions for certain tasks, or games, or even clinical interventions that are geared towards supporting the emotional well being of the user. But as you can imagine, these are not the dominant deployments of affective computing, we mostly find affective computing now in industries like recruitment and marketing. So for example, companies like Unilever, and many others use emotion recognition devices in their hiring process, in order to analyze certain nonverbal responses and facial expressions, which they say are indicative of certain desirable or undesirable character traits relevant to the job. However, you won't be surprised to know that this has come in fairly heavy criticism. So there are certain worries about this technology. The first worry is that it is simply not functional, that it's based on bad science and that it doesn't do what it's supposed to do. And closely related to that is the various kinds of ethical concerns, mainly that these systems are in danger of propagating certain kinds of biases and prejudices.

So Lisa Feldman Barrett, for example, who is a major leading light in Affective Neuroscience has come out fairly heavy against this technology. She's labeled it Neo phonology and said that there's simply no way that it can do what the people who make it say it can do. And this is because she says it's based on a very outdated theory of emotion, which states that humans have six to eight basic emotions, things like anger, fear, disgust, surprise and so on. And that these emotions are expressed through sets of facial expressions, which are universal across different cultures in different contexts. And anybody familiar with Lisa Feldman Barrett work, will know exactly what she thinks about that theory of emotion. She's not a fan of it at all. And the ethical concerns have been raised by AI ethicists like a Berber Biharni who's argued that basically the fact that these systems are trained on very large datasets mean that they are inherently conservative. And this is why they propagate certain biases.

So the two pictures of the hand holding a device you can see on the right hand side, in this case, it's Google's vision cloud. In the top picture with a dark skinned individual, that device is identified as a weapon. And on the bottom, that light skinned individual, it was identified as some kind of electronic device. And there are other studies as well that have shown that emotion recognition technology works completely differently on non white individuals. And so with technology like this making such consequential decisions for people's lives, it's really important that we start to get this right. And we don't have these outcomes that we have in the current program. So we need the strongest most up to date, theoretical independence that we can get. And we think the place to start in updating the science is to recognize that these devices are very problematically disembodied, they're very superficial, and they are inactive in the sense that they don't perform any actions. And this, of course, is a million miles away from the way human beings interact socially and emotionally. And we've known this for a very long time. So we've known for example, from Louis Pessoas work that emotions are not simply partitioned off from the way human beings think or act, actually, cognition and effect are very closely intertwined. There's no discrete separate brain areas that only do emotion and only do cognition. And furthermore, research paradigms in cognitive science. So embodied cognition, for example, tells us actually, we need to go even further than that, and recognize that embodied action is an integral constituent part of how we think and feel, and then the other ease that make up for your cognitive science. So in activism, extended cognition and embedded cognition have come together with niche construction theory and really interesting ways to tell us that actually, we also need to consider how elements of our external environments can scaffold the way that we think and feel. So this is where active inference comes in. Because we think that if we're serious about designing these kinds of devices, taking into account these most up to date theoretical developments, then active inference basically brings all of that in with it. So **active inference** is a theory that really elegantly intertwines action, perception, thinking, cognition and effect together, under the unified imperative of minimizing an agent's surprise.

So that's the first thing that it gives us off the bat, it gives us this unified computational, unified conceptual framework that can be shared by researchers in different fields. But mainly, as the name suggests, active inference really puts action front and center, it's not some afterthought, or some bolt on gimmick. It's worth reflecting for a second, on how central actions are to the way that we interact socially and emotionally. So human beings are very far from being a passive classification device. We're constantly sampling the world and probing the world in order to get more information so that we can update our models of the world. So imagine the following scenario, which happens to me fairly often. Imagine you're on public transport, and somebody's giving you a weird look. Or maybe they're scowling at you in some way. We tend to not sit there and look at their facial expression to try and work out what's going on. We have other avenues open to us. So we might look behind this to see if they're actually looking at someone else. We will probably look at the broader scene for some context, to see if there's something going on that can tell us more about that scowl or depending on our mood, we might even scowl back at them or flash them a smile and see how they respond to that. And another scenario that really brings this intuition out very strongly, is to think about the peculiar tension that comes in a job interview.

So that tension is the result of a confluence of two things firstly, very high uncertainty, uncertainty that's really important to us. And also the fact that our usual embodied epistemic resources have been straitjacketed by social convention. Because it's the case that in a job interview, even though we want to know a lot about what the other people are thinking and feeling, social convention dictates that we can't ask them, we can't prod them. And we can't really sample the scene in ways that are going to give us more information, we're stuck to the chair, we have to wait and see. And that's an unusual situation to be in. Because so much of human social and emotional interaction relies on active states, to use active inference terms. So speaking, listening, prodding, smiling, scowling, raising an eyebrow, all of these things are embodied actions that we take to learn more about social setting. And the thing to emphasize is how important context is, as well. So the ability to actively survey a scene to drinking context. But also, the way we learn about the relevance of that context is something that's built up and scaffolded through action and different kinds of patterns of practice. So if you think about the scanner on the bus, again, there's a high degree of uncertainty around that facial expression. But if you imagine that same facial expression transported onto the face of somebody on the other side of a boxing ring, all of a sudden, the uncertainty around that facial expression is minimized, because the context of boxing ring tells you everything you need to know, about why that person is scowling at you.

And this emphasis on context is something that's badly missing in current iterations. And the act of inference community is already producing really cool work premised on these kinds of insights. So there's this paper 'thinking through other minds' by Samuel wscf, and colleagues. And this paper highlights how it is that we come to understand our socio cultural niches through precisely this active social foraging. So it's really emphasizing the importance of context. And the fact that we come to learn about context through action. And there's an example of where we see a gap between artificial systems and humans, when dealing with context is, how artificial systems and humans compare when performing selective attention in regard to some task, so it's a really pervasive problem in artificial systems that they don't tend to look at the same places that human beings do, when human beings are surveying a scene for some task relevant information.

So the question is, how do we get artificial systems to drink in context in the same way that humans do? And then how will that improve the performance of emotion recognition devices? So selective attention is all about filling in epistemic gaps. It's about filling in gaps, in your knowledge with information from a scene that may or may not be task relevant. And one of the reasons humans are so good at this, because obviously, we have this huge knowledge base of what different contexts mean, we live in the world, we've always inhabited socio cultural niches. And so we have a lot of experience. But as I said before, it's important to emphasize that the way that we learn about contexts, is about sampling different contexts. It's about the fact that we have our entire lives been actors in the world, not passive observers. And this work by Mercer and colleagues that you can see on the slide here, it's really interesting, because it shows that active inference is capable of modeling selective attention in ways that give us much more human like results. So they use certain kinds of internal precision dynamics. And they demonstrated that these precision dynamics can map accurately, covertly, task relevant and task irrelevant features of the scene, and then update precision estimates in relation to that information, which then drives overt actions, which then serve to update the systems model. So it's this very close relationship between covert attention and overt attention, which is really interesting on this account. And active inference is a really powerful framework for recognizing and addressing context generally, and for the importance of action in learning about context.

So the models that I just outlined, they provide the tools for this very elegant top down first principles approach to selective attention, which is based on these internal precision weighting dynamics but also on embodied action perception cycles. And of course, one side effect of this is that systems based on this would be able to autonomously select the data from a scene, which is going to give them the most epistemic payback. And this means that they can do away with the very large data sets and long training times, which AIFSS have said, are probably the root cause of a lot of the ethical concerns that I talked about earlier. And so from a practical standpoint, this means that we need to think about building effective computing devices which are not merely in a lumps of plastic, we need to start thinking about approximating something much more like a fully embodied agent. One consequence, that's really fascinating about the active social learning that scaffold through other minds that I was talking about earlier with the thinking through other minds paper, is the act of inference agents can come to enjoy a degree of synchrony between their internal states.

So this paper by Karl Friston and Chris fifth, a duet for one, it utilized simulations of songbirds to show that quote, 'generalized synchrony is an emergent property of coupling active inference systems that are attempting to predict one another'. So in rough terms, what they demonstrate is that according to active inference, meaningful communication between two agents requires that they are sufficiently able to model one another in an infinite regress. So what it is? it is me modeling you modeling, me modeling you. And that by doing this, by making and testing these kinds of predictions, we ultimately converge on model synchronization. And this is a core part of the original paper by Daphne, Demacus, that she did with Friston and PA, which has already suggested that if we take active inference as a starting point for building affective computing devices, then what we have, is the prospect of an artificial system, which can potentially sync internal states with the user. And that's obviously going to hold an awful lot of promise for certain applications that affective computing. And I would say to anybody interested in the things I'm talking about, now to go and start with this paper by Daphne, because it's a really interesting and wonderful starting point. But one thing that we want to say is that for this deep, affective synchrony between artificial devices and users, it means that the artifact itself will need to have some interoceptive signals, some internal affective dynamics of its own. And it needs to be able to act in ways that expresses those signals. So far, I've been talking about acting in ways to express those signals and acting in ways to sample the environment.

But I want to say something now about the prospect of active inference devices, which actually have their own internal affective dynamics, because I think that the act of inference framework has already shown the potential to provide this. And what I'm talking about here is some fairly recent developments in the framework called **aerodynamics**. And using aerodynamics, we can start to understand how embodied affective states are an intrinsic part of the motivational drive for curiosity and epistemic foraging. So one of the really elegant, famous strengths of active inference is that it has the power to dissolve this opposition between explore and exploit. And while there have been numerous strategies for building the motivation to explore into artificial systems, active inference has the potential to put embodied activity and emotion, right at the center of solving that problem. And so this is obviously going to be relevant if we want to build emotional recognition devices that are intrinsically motivated to probe the internal states of their users. So it's worth taking a second to refresh how active inference accounts for emotion in effect. So, **the first attempts** to understand interoception in active inference were, they bear a lot of resemblance to the way that we were thinking about perception under active inference. So it was about predicting signals, hidden states in the world, except that the signals that the brain was trying to predict where internal signals they were coming from inside their own body. So gastrointestinal, respiratory, circulatory signals, and feelings like hunger, thirst, temperature, pain.

These were seen as top down predictions about the hidden causes that underlie those physiological changes. But it was the case that researchers that were working in Affective Neuroscience, so people like Lisa Feldman, Barrett, Neil Seth and Mika Allen, they were quick to add that these interoceptive predictions probably held a special prioritized place in terms of the overall system, because they will likely to ground other predictions, predictions about the external world in terms of what really matters, which fundamentally is maintaining the homeostatic states of one's own body. But more recently than this affective states have been hypothesized to fill another role within the active inference framework, which essentially says that felt bodily states things like mood and other affective states valence bodily states, they reflect a second order information within the dynamics of the active inference system. And that information is essentially tracking the rate at which surprise is being minimized, relative to the expectations of the system. So according to aerodynamics, affective states are essentially the subjective level feedback, about how the system is doing at minimizing surprise at keeping itself within expected bounds, relative to the expectations that we had going into that scenario. But the second order information, it's not superficial in the sense that it reflects that information. But it actually plays an intrinsic role in modulating the internal precision dynamics over action policies. So from a phenomenological perspective, this makes really intuitive sense. So when we're doing better than expected at a certain task, we tend to gain confidence, we might take more risks. And when we enter a certain scenario or task, with a particular action policy, which doesn't work out the way that we expected it to, we will be very quick to switch things up and try something else.

And in this sense, aerodynamics can be set to keep agents flexibly attuned to the opportunities for success within their environment as they learn and develop new skills and abilities. And the thing to notice is that agents that are outfitted with a sensitivity to aerodynamics are naturally curious. Because finding new surprise in the eye environment which can be successfully minimized, it literally feels good to us. And the places where we find surprise that we can minimize, in the greatest amount is at the edge of our skills and abilities. And this is why we like to find scenarios that are maximally challenging without being frustratingly challenging, without being too hard. So we like to occupy areas that are neither too well known nor too complex. And aerodynamics also plays a role in helping us to direct and enhance learning. So price, and it's reduction rates signal, the expectations about the learnability of particular situations. So that helps to guide our attention and prioritize certain areas or certain tasks, where we know we can find the most success. And we've already seen this optimal surprise minimization show up, in robots in terms of curiosity.

So there's this work here by Odoya and Smith, where their robots were trained to seek out optimal levels of complexity, where the most learning can take place. And specifically, now, there have been active inference approaches that have begun to use aerodynamics in real world robotics. So this is really exciting. And this is real world proof of concept in the work of skelassi, Lara, and Syria. And these researchers have actually built robotic systems that make use of this internal aerodynamics machinery. So their work has shown that robots that are equipped with aerodynamics are actually better able to manage uncertainty by fluidly selecting adaptive actions in an environment compared to more traditional approaches. So artificial agents equipped with internal aerodynamics, are better able to learn, and then autonomously select the proper surprise minimization strategies in any given situation. And they do this by allowing their valence states that second order information about performance relative to expectation, to weigh the selection of the most suitable behavior. So in other words, by allowing that second order information to have a direct impact on the internal precision dynamics over action. And this work showed that this internal aerodynamics also provided a way for artificial agents to navigate the temporal aspects of goal selection. So basically, what that means is these agents were very knowledgeable about how long they should persevere with a certain task, and when they should give up, which is obviously something that even human beings struggle with a lot of the time.

So thinking in terms of aerodynamics, it shows us that effect is intrinsically linked to goal selection. And we want to suggest that, by introducing these aerodynamics into affective computing devices, we would start to see devices that are not only motivated to exhibit a curiosity, in implementing new policies for action, but we'd actually start to see a real paradigm shift in the affective computing program to a much more biomimetic approach. So instead of having classification devices, in lumps of plastic, or in smartphones, we'd start to see embodied devices that can actively engage with the world, and that have their own internal affective dynamics based on what we think is going on in living systems. So this is really exciting. And this new wave of affective computing devices would not only be able to perform much better, but it might go some way to addressing some of the ethical concerns that I was talking about earlier. But the thing to be really clear with, or a disclaimer at this point is, we are certainly not saying that an active inference Approach to Effective computing is a replacement for thinking about all of the social justice issues that come with the implementation of this technology.

We are speculatively saying that on first glance, it certainly appears as some of the ethical concerns might be addressed by this new approach. But there are going to be a lot of benefits of this new approach. So first, if you think about the kinds of models synchrony, that I was talking about earlier, and think about that within the context of therapeutic intervention. We think that when we get this degree of model synchrony, any dysfunction in the user's internal dynamics is going to be mirrored in the internal dynamics of the artifact. And so this is going to be made the device very well placed to make suggestions about potential interventions. And this is essentially what CBT already attempts to do. So this will be building on approaches that have already been proven to be effective. And the next thing is to think about the fact that so far when we've been talking about action, I've been talking essentially about **epistemic foraging**. But once you have the possibility of humans and artifacts establishing this kind of model synchrony, and you have these artifacts that are properly embodied and able to act in the world, it might be possible for the artifact to begin to install prior preferences about what states in the agent are actually preferable, such that the artifacts may actually be able to steer with a degree of autonomy, the emotional synchrony between it and its user, to specific ends. So when we have these active inference theories, beginning to emerge of depression and anxiety and other disorders. With that full understanding coupled with the model synchrony, I've been talking about, we start to open up avenues for the device itself, steering the user away from these dysfunctions. Now, it might be the case that these active inference devices come with their own set of worries and ethical concerns, It's very plausible that they do. And it's something that we're going to be thinking about as we go forward in this research. But I don't have time to explore it here.

But the last thing to say is, most speculatively, is that this act of inference approach also sets the stage for beginning to address the well known value alignment problem between humans and AI devices. Basically, what we have here to our mind is a initial and very speculative building blocks of building artificial systems that have a degree of genuine empathy with their users. So these devices would not merely be simulating empathy, or passively categorizing human emotion, they would genuinely have their own internal dynamics, that would synchronize and match with the internal dynamics of a user. And this is going to be a bedrock for much more interesting and much more rewarding human, AI collaboration into the future. And that's the end. I wish I could be there to answer questions. Unfortunately, I'm not, I'm pretty sure Mark Miller is going to be there with you. So maybe he would be happy to answer some questions. But I would also encourage you to get in contact with myself. I'd be really happy to hear from anybody that's interested in this stuff. You can see my email there b.white@sussex.ac.uk and you can get in touch with me on Twitter as well at midnightbiscuit. Thank you again for listening. It's been a real pleasure to get to present this work. Thank you very much.

[editorNote: "2022 Robotics Symposium 1st Session ~ Part 4"]

[section: "**PRESENTATION TOPIC: 'Learning Agent Preferences' with Noor Sajid"]**

[sp: Friedman]

1:34:08 This is the presentation of Noor Sajid **"Learning agent preferences".** Thanks, Noor, for joining and take it away.

[sp: Noor Sajid]

1:34:24 Thank you, Daniel. So before we get started, I wanted to thank Daniel and the active inference conference for inviting me to give a talk on this project. I'm really excited about that. So to introduce myself, I'm Noor, I'm a current PhD student at the Welcome Center for Human neuroimaging with Karl Friston. And this is some work that we've been thinking about over the last year or so. Do we have questions throughout the presentation? Or are they at the end?

[sp: Daniel Friedman

1:35:03 We'll be taking questions in the live chat. And then at the roundtable will be bringing them up, not during your presentation.

[sp: Sajid]

1:35:19 So the project is focused on **"Learning agent preferences"**. And from my perspective is super interesting, because that social changes the dynamics of how you consider the problem setting. And that's what I'm going to start off with. But before I do that, I wanted to highlight to my wonderful co authors, that I'll be presenting the work on behalf of, so we've got Pannus, Alexey, Zaff, Lance and Karl and the project. So the work that I'm presenting is based on two different projects, and I'll highlight the different work as we go through. So the way the presentation is going to be structured is, I'm going to briefly motivate the problem setting and then describe the problem setting in a bit more technical details. And then really drill down into exactly how we can learn these preferences, that we can equip the agent with, and then some experiments and remarks. So what I wanted to highlight is that when we learn agent preferences, there's usually a bi directional association between the the agent and the environment. And what I mean by that is, something that you can see in this graphic really clearly, so you've got the main part, that the agent would have taken, as it was walking down this particular route, when hiking, but as perhaps many other people are joining along, the agent ends up walking along the shorter or maybe the more smaller part.

So what this highlights is, that agent preferences are essentially dictated by the environment that it's surrounded by. So depending on the constraints, so for example, other agents, maybe an animal or something else happening on the road, would mean that the agent ends up taking the second part instead of the first one. And as a consequence of that, it changes the environment, as more and more agents do the same thing, the shape, or the construct of that part becomes more prominent, and it becomes part of that environment. And what I'm really interested in as part of my work is this bi directional association between how the agent changes the world. And the world changes the agents preferences, because it constrains the actual state space that exists and but as part of this project, and one that we'll be presenting, we're purely focusing on how the agents preferences, or the how the agents as objectives are change as a consequence of the environment constraints. But before I do that, I really wanted to highlight what preferences actually are, because a lot of the time, we're not really aligned on what that means. So I'll just briefly describe how we are considering preferences. So preferences here are usually a subjective assessment of what agents would like to experience and this can be continuously land or modified even in the absence of external feedback. So there might be some internal motivations or some objectives that the agent is learning internally, that shaped exactly how the agent wants to behave in the world. So in the previous example, when we were looking at the case of going between the two parts, depending on the constraint that the environment, is essentially as the agent subjective preference, because it could have taken another route which so for example, maybe here and that could have also shaped the environment as well. So let's motivate this problem setting slightly more formally. So we're going to be working as part of the idea that these agents that we're interested in, have an internal model. And this internal model is composed really briefly of three important components. So three important random variables, and then one deterministic variable.

So let me qualify that a little bit more. So we've got our outcomes. So this is something that the agent is exposed to, in the environment. And, for example, the actual constraint in the instance of the hiker being having to choose between the two parts, for example, it might see a hindrance, or it might have some grass or some, other agents that are exposed to and that's the data coming through. And it needs to then identify whether it wants to choose one path or the other path. So that would be based on its own inferences about what that outcome actually means. So that's denoted by S here. And then based on that, it needs to then decide what action to take. And that's been noted by the VA here. And at the same time, the agent is keeping track in this particular formulation of the agent's model, or the gender model that we interested in, which is denoted by this deterministic variable h2, or h3 depending on which time point we're interested in. This deterministic recurrent model that we have, that's encoding or the prior history, the actions and the states that the agent has been exposed to and already has selected in the past.

And that encodes what is the updates, that are then use to select the posterior estimates for the next time point, then in this particular model, you've got your latent state and prior, and we're calculating them in really a specific way. So your prior is defined as categorical distribution. And this becomes really important for us because this allows us to use some conjugacy rules to update the way the agent's preferences are learned. And I'll come back to what I mean by preferences in this technical session a little bit more, on the next slide. And the state posterior here is, again, a categorical distribution that the agent is estimating based on the history and the current observation it's been exposed to. And we've got the standard formulation if you're working within a MDP formulation, where we got a transition function. So this is denoted again, as a categorical distribution, conditioned on the history of the agent, the agent is encoding. And then we've got an image predictor that determines exactly what would be the next observation given the history and the state. So the idea with this gentle model is that you have an encoding of how the agent is representing the world. It tells you exactly how the outcomes are then inferred as particular states that are then allows the agent to evaluate particular actions, but I haven't really defined how the actions are selected. So we work in a standard active inference setting, where the actions are defined as being sampled from some probability distribution A, so the actions we saw before, which is calculated as the **arg max of minus 'g'** **over 'a'**. So what is that exactly?

So for our work, we were interested in essentially extending the minus, the expected free energy with a conjugate prior. So the expected free energy and standard terms would be something where you have an extrinsic imperative, you have a salience formulation, and you have novelty imperative. It's something that's constrained by the environment. Saliency is when you want to have accurate belief updates. And novelty is when you want to be able to estimate your world appropriately, given the parameters of the model that you've been able to learn. And when we extend it for the preference learning setting, and this is something other folks have done, maybe introducing it as part of prior over the outcome space. So we're looking at as part of a prior over the state space. So this is the prior and we're conditioning on a categorical distribution 'D', which I highlighted before, and that allows us to use some of the contiguity rules of interest. So what do we have so far? Before we move on to how do we actually learn this 'D' that we were interested in the previous slide? So we have an agent who's equipped with the model, the agent is interacting with the world. And based on this interaction, the way the agent is learning its preferences can shift. And the way it's shifted, is a consequence of the type of actions it's making, that we had using the expected free energy.

So how do we learn preferences? So in the psychology literature, and some of the spiking neural networks and other formulations, there's been a few different ways, it's been proposed how agents are learning preferences. So one of them is mere exposure effect. So the idea that when you're seeing something quite frequently, that pairing is more preferred, then if you want, seeing that, and this can be categorized as a heavy plasticity learning rule, then you've got attention mechanisms, where when you're attending to an option, a becomes more preferable, so maybe you're selectively looking at 'X' or 'Y'. And based on that, you filtered out all the other data that you've been exposed to. And that's what becomes more something that you as an agent would prefer. And if you were to think about a more biological construct to that, that might be a consequence of some synaptic gating, that can encourage the enhancement or some sort of suppression of the data or the noise that you are exposed to. Another formulation could be the **contextual** effects, where an option is only preferred, when it's compared to some other options. So there's this relative comparison happening. And based on that, in certain settings, you would want to do 'X' instead of 'Y'. And here, 'X' could be taking the part, the wider route in comparison to the maybe the tiny route that we saw in the hiker picture. And you only prefer the wider route when you don't see any animal or some blockage there and this encodes the behavior relevant signal selection for the agent. So now I'm going to go through some rules, and some formulations that we've been thinking about in terms of encoding preferences. And the way we've prioritized the learning of those preferences, it is aligned with some of the things, people in psychology have also been thinking about.

So the first one is learning preferences from your exposure. So we start off with extending the agents gender model with a conjugate prior over the prior beliefs. And what that simply means is that we take the category of distribution that we've conditioned our prior state on. And then we introduce a prior over that. And that allows us to take into account some of the controversy up to rules that we're interested in. Because our prior distribution over the state space is D, which is a categorical distribution, we can now define a judicial distribution as a conjugate prior, which is denoted here. And we've got two different formulations here, of how you can update that. So essentially, as you're exposed to more data, you're counting your suitor counts over the summation of all those suitor counts, in that particular factor that you're interested in. So taking this into account, we have been learning rule, which we do using online interactions through preferences.

So the way it works is that given your hyper priors in the time point before, you can update those, based on some learning alpha, and also the belief updates you've had in the past. So this is denoted by the S, For the particular pseudo counts or the territory parameterizations for this current time point, and you add all of this together and that gives you the updated preferences. So the way this particular formulation works is that the more you see something, the more you're going to prefer it, because there's a very simple learning happening here. And in the simulations and the way we formulate that the moment, we've got Alpha set as a static parameter equal to one, so you can manipulate that and you can manipulate it, where if you have a alpha going to greater than one, you will then weight, the new data coming in a lot more in comparison to, if you had it for less than one, then you're not taking into account the weight of the new data coming in as much. And what this allows us to have is accumulation of particular contingencies, or the way we are privatizing are prior. And these dictate the lunch preferences. The next formulation of learning preferences that i wanted to speak about was, how we can learn by attending to preferred options. So here, we're going to slightly change the model by introducing an additional preference learning component, so we again are extending agency enter model with we conjugate priors over the prior release. So the hyper price, so this is exactly the same as before. But the different thing that we're adding here, is the synaptic gates in paid preferences. And these are computation homologues that we've introduced. In terms of the actual biology of formulation, that's open to interpretation. But these allow us to have an attentive mechanism, which is what we're interested in. And we do this to a two step procedure. So first, we encode memories and how that works.

So the way the encoding of preferences is working is we have two components, which we then combine them together. The first component is the the online exchange that the agent has had. So the by online exchange, I mean, the agent is selecting its actions based on the expected free energy. And that's allowing you to essentially gather data about all the different trajectories are follows depending on what action is taken. And it's got the data and its posterior estimates given that. So this would be the on policy. And the second bit that we have is the imagined interactions. So this is when the agent is offline, in the sense that it's no longer being exposed or given outcomes, based on this imagined or the way it's interacting with the world. And the only thing it's getting is the the updates in the States, the latent space depending on what actions it's selecting, and this is the imagination part. So what we're doing is we're combining this together. And we take 30% of this, and all of this.

So these are 10 steps into the future. And then we're essentially interleaving them together. And that gives us an encoding of the memory. The reason for only using 30% is to allow for imagined interaction or preset things that the agent is considering to be taken into account. And the idea with the interleaving is that we're allowing for both the real experience and the imagined experience or the real, is here the policy experience to be used to shape the way the agent is. Encoding is perception of what has happened in the past. And then using the encoded memories, we then encode the preferences using a selective attention process. So this memory buffer that we have here is, what I showed in the previous slide. So this is the memory buffer. And then using this, we essentially encode the preferences using two gating mechanisms. So the first one is an intention block. And the second one is a gating block, the attention block, essentially weights, some part of our distribution slightly higher, and then the gating block, constrains or restricts that data out by filtering it. And we are optimizing these two blocks using maximum entropy. And the idea with optimizing through maximum entropy is to allow for some shifts in what's happening. By shifts, I mean to have a more flexible representation, because we're trying to maximize the entropy of the distribution. And this formulation allows us to encode filter contingencies that can dictate land preferences, this is a slightly different formulation built on the same Bayesian updates, but we're introducing this selective memory component. I'm going to quickly go through the experiments. So we evaluated this, the two algorithms in a 16 by 16, by 10, grid world. So in the example grid is here. So the agent is presented with this image, including his own vacation at each time step. And we've got four distinct states. So we've got red, we've got blue, we've got the light green, and dark green as well. And in this particular formulation, we have no reward or score outcome modality. So the agent is learning purely on its own motivation to understand the world. And if there are questions about that, we can talk about it. And the grid is changed every case steps, and the key determines how volatile the environment is. And at each episode, the agent is initialized in some random application. So maybe here or here. And that constrains how it interacts with the world.

So for sake of time, I might skip this bit. But essentially, the tables are highlighting exactly what the training parameters were. And they were fairly consistent, actually exactly the same between the two algorithms. So the pepper formulation, where we have had been plasticity, and another formulation, we're doing non reinforced updates using selective attention. And then the preference learning parameters, that how long the planning horizon was, so it was 15. And we have an episode length of 100. And we do this for 50 episodes, and we reset K, K is reset every 1, 25, 50, 75 and 100 steps. And this gives us a nice way of evaluating what's happening. So then the first thing we were interested in was evaluating how the preference are shifting in a static setting. So this is one where we have Hebbian, so this is learning. And this is where we have the attentive gating measure here and with the hebby and we can see. So this is the on the x axis we have the states dimensions, and the y axis we have the epochs or the time consideration. And this is the same for both things that we've seen at the moment. And we can see what the Hebbian one that as we go further down, it becomes more concentrated. And there's no really shift here. Whereas for the attentive preference setting measure, we've got these random blocks that appear that weren't there before, but also disappear. So it's quite interesting that over time, the preferences are shifting as a different measure, if you're doing a qualitative assessment of the comparison between the two.

And then the content, our **Post Hoc Analysis** of trying to actually understand what is happening quantitatively, we compared the heavy learning formulation with the attentive, selective attention preference formulation, and then we compared it with the baseline, which is the expected free energy of G, here on the y axis, we have the environment volatility, again, this is the K but denoted as percent. And then on the y axis, we have preference satisfaction and explore ancient trade off that we're using as a distance. And this is evaluating how far particular trajectories have shifted. So what we're comparing is whether there's an increase exploration or not, depending on which preference metric we're using, because of the based on our qualitative assessment that we saw before, there is this shift between the different encoding of preferences given the preference formulation that you're using.

So we can see that when we get to 50%, volatility, there is this shift from exploitation to exploration for the pepper algorithm. So we see that here, based on this nice mode of the distribution that we're seeing here, whereas for the new formulation is slightly expanded out, but it's not as exploitive as the pepper formulation. And then, when we are looking at the extreme ends, we can also see that there is this shift from exploration to exploitation for the pepper formulation, but we don't necessarily see it for the more formulation. So at the moment, there are some quantitative differences in the way the two agents are evaluating encoding preferences and how that shapes the behavior. And this is an example of the nore formulation in terms of how much it's exploring the path, and the ways it interacted with the environment.

So these are the grid worlds. And this is a heat map of that exploration trajectory. And then I'm going to quickly do some takeaways. So both of the formulations that we have, even though quantitatively and qualitatively, they are providing different ways of encoding preferences, they do have a tendency to influence the agent behavior that's different to the baseline of the expected free energy, where you didn't allow for this change in preference assessment. And if we are to compare with the standard reinforcement learning setting, we are here casting what is preferred to an agent instead of the environment or the designer. And it's particularly important in a robotic setting where you want to be able to go back and allow the agent or a robot to be able to shape some of its own goals and objectives. Purely if it's working in a more creative setting, maybe in settings where it has to do a really specific task, this type of formulation might not be the best. But there's provide a flexible formulation, where we're only modifying the preference learning component and using the same gender model. So the initial gender model that I defined for the agent is kept consistent for both the pepper and Nore formulation. But the behavior that we're getting is through this additional component that we add. But the key thing to notice that these preferences are a consequence learning a suitable gender model. So if your gender model isn't that good, then the way you would learn the preferences themselves might not be the best. So there's a slight trade off, because whoever is designing this formulation, or working with this formulation needs to take into account how well the generative model has been encoded or launched by the agent. And on that particular note, I'm going to end the presentation. So thank you so much everyone for listening. And I want to thank my co authors for this great work and my funders, and I've got the QR codes for both the papers if you 're interested. And that's it. Thank you.

[sp: Friedman]

2:02:17 Thank you. So you can depart the room, and you can rejoin for the roundtable if you'd like. Otherwise, thanks again for joining.

[editorNote: "2022 Robotics Symposium 1st Session ~ Part 5"]

[section: "**PRESENTATION TOPIC: 'Dual Control for Exploitation and Exploration and its Applications in Robotic Autonomous Search' with Wen-Hua Chen"]**

2:02:39 All right, the next talk is going to be by **Wen Hua Chen**, **"Dual control for exploitation and exploration and its applications in robotic autonomous search."** We're back with Wen-Hua Chen. Thanks, again for joining. And please take it away.

[sp: Wen-Hua Chen]

2:04:23 Thanks for inviting me to this particular meeting, is quite interesting for me. As I'm not always operating this particular community. So thanks for providing me this chance to share my working experience with you. So my talk is about 'how to develop an autonomous search strategy for robotics, and investing at a context about chemical biology and other interesting dispersion’. So the approach is dual control for exploration, exploitation, and as you will see is actually be a lots of a similarity that with the activity inference theory. So I came from Loughborough University, I'm working in the aerospace and automotive and union department. So I have quite a strong engineering background, but not on the neuroscience. So, this is a basically outline of my talk. And I can share you some background about the application and also discuss the design method, and then talk about the simulation and experiment results.

And also particularly I'm interested in to share with you about my thinking about, what are the relationship between the approach we discuss here, and also the activity inference, reinforcement learning and other similar area, and then talk about what is a way moving forward? So, let's talk about the **autonomous search** as a case study. So, this is to basically wider find in the natural environment, and for the polar bear, they try to find the prey or the food and they need to use smell and also similarly you can find the insects if they are matting and other food, they can use similar kinds of study. The idea here is by making use of the sensors, the idea the sensors that are near to reasoning here is about where the food or the sources might be, the only thing about what is the best strategy in order to find it. And particularly interesting for us is how to convert this into intelligence from natural world into the engineering area. So we are able to teach robots or you always trying to search any chemical or beverage and the resources and also in the future you can be using for environment reinforcement, for example, try to find approaches where sources and many other application. So basically, you can think about it. The idea here is somehow like we tried to develop a smell dog, which can slip around and then try to find drugs and other dangerous materials. This is not a new area, there are lots of research in the area, in particularly bio inspired lots of research. People can be using chemotaxis and the other reactive strategy like you fly down with the wing, if you find that something, you try to follow the chase in order to search that.

There's also another mainstream working in this area is based on, we call the information theory approach, which is you treat this process as a information gain process. Somehow, at the beginning, you don't know where other sources and you have a high level of uncertainty, then during your search, you drive the level also in the lower and lower. So this is actually is that you can think about it, this is an information gain under them, using the reward function like entropy, like KR divergence of any others to measure the success of your search. And then based on that, you can derive the strategy to drive into this, but now not we're looking to another angle and in which they as a control problem. And then think about how to link this with active inference and the same work. So when we try to search the source and you don't need any information, so basically on the robot, you have a chemical or biological agent, there's a guess sensors, and then based on that, every time you need to read any, where you need to move your robot, you're to have a best chance to find the source. So, there is a strong interaction between that robot and the environment and the vulnerable and also they have a strong interaction component between the perception and in any decision making.

So basically is for you designed to go to a different location, and then you will take a different chemical sensor moment, this will affect your belief about where the source might be. And this will also change your course of action, because based on that, you need to decide where you want to move the next step. So, there is a strong correlation between the perception and the planning or action. So, this is also a typical example of like a trade off between the exploitation exploration, so in here to maximize your chances. So, a lot of people in this field must be familiar with this trade off, I will not go into the detail. Now, I will try to explain to you about a strategy that we have developed. So now we'll try to formulate the problem and there are method here and there are some methods here, you can ignore the but try to understand the high level understanding, what our math here is, each time we have x which is the state of an agent of the robot, and also you have a variable set of action you want to take and the wish is the basically you tried to make the robot to move forward or backwards or left or right, to move to a different direction with different step size. And also you have the moments, the moments in this case is that you are firstly the guess moment on the sense that you can have a chemical sensors on the robot and also you have send moment about your position or your location with respect to the environment. And the other things that we have is the unknown information about the source and also about the environment and which will include the location of the source and also include constant environment like the wind direction and the speed which will significantly affect the dispersion for the chemicals or any audio. So, the idea here is you take the connection or the data during the process and which you include the anytime the action you take, which is you and also the senses as a way of thought which is added here.

So you add it all together, give you something we call the information state, which is a connection about the all data you have so far, and then we decided what is cost function or reward function it should be. In the simplest way do you think about okay and my aim is to try to move my robot position close to the source of the location as close as possible, which is quite a sensible the mayor, but in the problem now is, I don't know where the source is, location of the source is. So, this is why the condition for the data to connect and so far. So, condition on this is, I try to minimize this cost function which is a typical way in our control community, there is a particular name called the stochastic MPC model predict control but what we do want to do is, we want to move away from this, we want to do further and because with this we will further, this is actually a bit of a link with active inference. So, what are we doing is now, we are not the conditional on the other data we connect so far, but also we connected on some virtual data. So, whether the basically we also added the future or the actions and what are that future outcome. So, to sum up, because you have a model, is that if I do this, what is going to happen, what sense measurement I'm going to get, if I do another thing, what measurement I'm going to get and how this man will affect my belief of the water, of the environment.

So, that I now conditioned not only on the IK, but also condition on IK plus one and here we need to have take into account the contraction our future movements and how the future movements will affect our belief, but before I introduced the detail mathematic, a little more method, I tried to give you some definition on mutation. So, suppose anytime you have a probability density function of any unknown parameter theta, you want aspect this is a PDF preview density function, with that and if you take the mean the expectation, that the security something, we call the nominal estimation, use a mean of that as a nominal estimation and he tried driving your Europe maybe to the nominal estimate location as well. But also we have to quantify how uncertain level of this estimation, so how reliable your estimation of all of the environment, so, basically what defines the error between them and the nominal and from any measurements, then this will actually give us that as a variance, it will define the variance of this one. So, and then once we do have a decent notation, we can simplify the cost function we had before like here, but now is the condition of our 0k plus a one and they can seem to fit into two terms, the first term is about 0k, it maybe the activity invariance, we call the extrinsic value, the second is intrinsic value. The first part is 0k i want to move my robot location to that believe it or source location, which is denoted by the normal estimation, for your as a target location, you want to make this error as close as possible. So this is the task you want to perform something to the basically and move your robot close to where you believe it might be.

The second is how reliable this believe and we quantify here, by using the variance and should remember those two ranges is derived from the very best, the cost function, there is no weight between the two, is naturally this is the optimal way if you might minimize this, naturally is the optimal way to do it. So the cost function is consistent with two times a year, which is the task or the objective you want to perform and the uncertainty if you believe so, you have that extrinsic and also intrinsic values and optimally combine them together.

Now, we can go to a little bit more detail about equations and I will not go into too much, but it basically is like a VC the best agency equation, because next time the robot position depends on the actions and also you have the dispersion model, which is somehow like a Gaussian model, but it is also dependent on a number of parameters, which is the wind speed and wind direction, what ever can because they have some lifetime in the state of AI, under them some other parameters associated with the location of the source. But also we try to model the sensors and we shouldn't do that in the environment, that the chemical, and also those bio agents, and their colors are really low. And that many times you may be known, not able to detect anything. But also, you should also know they have a lots of local turbulence, which upset your sensor. So that means that lots of times you couldn't afford with a gradient method, it's hard to say, like I found a gradient, I found it the maximum concentration, no, it didn't work. This is maybe what it looks like, after the two dispersion fields, you can see the concentration changed quite dramatically. So that's the challenge. So we also need to have more than in the sense of behavior, somehow, like wearing the sensor, you can have a reading. So it's a true reading plus some sensor noise, where that many times you don't have sensor reading. So you purely have background noise of your sensor. So this is another point. And then once we do that, and we have the try to see what are the unknown parameters about the environment about source one estimate? So basically about include the wind speed, and the direct direction, and other things associated with the chemical components other then the parameters associated with a target, it is a source of location, the release rate, and then we can be using in our framework, we're using Bayesian inference to do it, try to estimate those parameters. So, this is what the diagram looks like. So, basically, you have two parts. One is about the reasoning, another part of it is the planning or control action, is the reasoning every time you take the new measurements, and the you based on the prior information, and the model, you have this framework, and you try to update it, you have penalties and estimating, and then you build up a previous map about your local environment.

And then you feed this into your planning, here you try to estimate if you take any kind of action, what are you influenced about to believe and always how to make your agents close to the source. So you do the planning here. And this red box is somehow like a try to using your virtual or a moment to do the reasoning and look at this again, and it gives you a division and then keep doing this. And so, you can do some simulation study about it is for example, if we started from here, this is source, this is color changing, and then we can put the source in different locations and as agents in different locations, to see how they are performed. And then try to understand the performance. And what we can see is that if we quantify the performance in two ways, one way is we call the successful rate, which is if we run the simulation 100 times on excellent 100 times what a successful rate.

So for the new approach, you can achieve about a 100%. And for the sum entropy based original our method you can achieve about 80% found that, if you were using classical motor control, you always have about around 80% of chance to find this, another, the measure is about a how piconet your conversion due to the true source of the occasion, which is denoted by a distance from the agents, to the source, in terms of the root mean square, because you run it many times, and what he can see, our approach is actually can decrease the very convergent to the source very quickly. And but others is all can slowly converge into that. And we're also going to do the experiment, this is excited by that you can put on a physical robot to try to let it wrong under them, you can do that. Using the software to implement the your high level argument at really low level, you have to have a control loop for the commander you're trying to follow driving and your high level decision to see where you want to go, the low level follow that we're using the sensors and also some low level control. So here's an experiment result, is very turbulent and changing quite quickly, the robot stuff on any points, and is purple points to give you an idea about it that you leave where the source by being presented by a particular field, as you can see with the time it goes they're concentrating too closely, and then to the location of this source. And after that you can make an area, give us an idea about a concentration in this particular area. And also we can do that if we flight outside using your implement ad all the strategy on the

UAVs. And the real test you can have the chemical sensor here, this is the order the GPS is a cameras and all the sensors, and you have a low level ground control station here. And they can do all the experiment outside they can. This is a trial on the chemical problems, they have a leakage of a gas, and then what happened. And you can see the test that we did and the industrial side and the UAV taking off. And they got to the chemical sensors on that. And they don't do it. And there were other sources based on that, they gave up some search strategy, for the first Assad, we did do the intelligent search, we add that to the UAV to fly around, try to pick up the data. And then we move through intelligent search and try to demonstrate so that pretended someone died because the chemical leakage under them, you need to center the UAV to identify where the problem, under them first respondent can take appropriate action to this.

So let me come back to the area, this is not an intelligent search warrant, but it justify rondalee connected data for understanding we can say, where they are, but then we move to a fully intelligent search then is somehow like hands off, you don't have anyone, that is you fully have to decide where to find to connect the data and then the child to understand where they are. So somebody could it be. And this is another scenario, I can see here and you have the car here maybe this is simulated environment, you have a vehicle involved in the accident, whether you have any petrol leakage or that because this is might be, it means you have a risk of the explosion. And then if you send the first responder to this area that were under the higher risk, so if you could have an agent to be there, try to search where have any potential leakage of gas and where that might be and we found one of them.

So that's the idea about doing this type of research. And then we also develop to extend this one to more broad applications, a particular one we call the self optimization control, that the idea is for any Mozart system, you want to maintain the operating best possible way, which you can change with the environment because when the environment changes, the best possible operation way but it changes however you want to have a system and by taking the same idea as we already talked about. They're able to explore the environment and influence on them. They are understanding how to best operate yourself. So somehow like here, they are changing environment, reward function. You try to follow that then try to do the best. So there's many applications, I talked about a one, this is a situation where we have the idea or energy, you have a PV farm, the energy that aim has a way of simple, he tried to harvest as much energy as possible.

But the problem is the optimal operation is changing with an environment that with a sunshine, the temperature, the solar insulation, have changed optimal operation. So what are we developing is strategy, no matter what kind of weather conditions, you always can operate the solar farm, operate in the best possible way it could be. So the red one is ideal to walk. The blue one is what we did is try to follow the optimal, this is optimal operation, we always try to follow. So that's some examples, not only for the autonomous search, but we can use this idea to so much wider range of problems.

Now we'll talk about that ratio with some others existing work, one is and there is a dual control concept, why we call dual control because the control action is not only changing up physical behavior of a US system, but also changing your belief of the world, of the environment. So this is why it is called as dual control but it however, is not a completely new concept in the control community. We did this before an event on a dynamic system or how to estimate your own state, how to estimate your own parameters. The idea now is try to extend it from UAV for example understand itself the cell is more to the environment, because we think about that for autonomous driving for the UAVs, we have all those information about ourselves. What we needed is the information about the environment and also their body environment. And then there is link with the active inference community. And this is a very interesting and surprising finding from me. Because the way am I developing a strategy, I don't have any idea about this community. And is that somehow like you can start from completely different area, a different angle, but however you found that you are landing on the similar idea or area.

So that's the one of the most exciting things in this research. So basically, you can think about is that you control the idea is also about it that you are actually changing your belief about the environment, and they use the to connecting information, this would be a game changer, your belief about that today is the interaction between the action and the perception and how they're connected with each other. So I will not explain too much, especially in this contrary, people may be much understanding what I'm talking about. And another is about that reinforcement learning. And this in my view about the link with the reinforcement learning. So basically, the reinforcement learning is trying to make an optimization for the given a dynamic system and subject, are given a reward function. And then you've proven yourself converging to find a solution for beyond an equation basically. And what a reinforcement learning though is, how to solve this problem by approximating the optimal value function. And also try to find it that often optimal policy. So idea is try to learn this by through iteration. But what we do is, from the work I'm doing is, developer from something we call the modus operandi control, we try to solve the same problem, but however with a truncated the Infinite Horizon problem into defining the horizon problem. So, every time we try to solve finding the horizon optimization problem, find the optimal solution. Reinforcement Learning try to do using the each iteration, like learning try to do that. So basically, and the whole idea about the link between them is actually experienced is in this paper and I published it. If anyone in the company interested in this. And please have a look. This is my view about a link between the two. And also it's a link with activity invariants.

So, because of the approach are different that I give you the conclusion, for the reinforcement learning, they have three major problems about it, one is needed lots of data to help them to learn the optimal strategy, optimal value function. And the second is once if you learn from the simulation environment, when the environment changes and however, there is a mismatch between your simulation environment in real environment, the optimal schedule you learn in a simulated environment, they are not working very well, in real life. Particular in this casem if I learn to search based on this environment, the wind come to this direction speed, I learned how to do it. But if you come to real emergency, the wind is actually blew to this direction, the strategy you learn maybe doesn't work at all, because it's not optimal. Another problem is actually that reinforcement is like a black box, it's very difficult to prove the stability or safety, this type thing. But we don't have either control, we have a rich body of tools, we're able to prove the stability and safety and other things.

The first tool is able to solve the by activity inference as well like, reduce the lump of data required and also have to deal with the unknown environment, but however, that control is always have another office, which is about safety about this. So, this is a quick try to think about the link between the process talked about here and the reinforcement learning and then we can discuss more itself for this particular talk, then the work we are doing, we try to move this from single stack to multiple stack looking ahead and the final horizon, but at this we have a problem about the computational load, because now we have to deal with a much higher compute, in the How To Reduce computation alone is quite a difficult. And last time, why am I talking with a car for instance, I gave me some ideas about the team how to do it, we I tried to learn from your community about how to reduce the computational load. Another thing is what we are doing is we try to prove a sense of a rigorous process, for the approach somehow like we try to prove they can converge into the true sources. And if you do anything, your believe can converge into two external environment under them and also you are able to prove the safety of that which is a particularly important for our area, when we deal with cars and aircrafts, we have to prove it is safe to do it. So we are working on in those areas. Conclusion is we develop some new framework in our way. And we tried to make system can operating on new environment by somehow like a trade off between exploitation exploration, and try to understand as a future action is influenced our belief.

So this is can deal with a coupling between the action and the belief. And then our approach is not somehow like many other approaches. So think about that. If we want the trade off your artificial stitches or intrinsic or extrinsic values together, add some weight, and actually this naturally happened, it is optimal in some way. And the particular reason therefore, as I think about it, is we have a particular effort for the community of active efforts. We have learned a lot from there, because you have a community here, people working in this area, developer, many good ideas, and the question is how to send it to that, how to promote more collaboration between those two committees, it is a very interesting to do.

2:33:34 So that's all of my talk, I very much come to the end of my time. Thanks. So I will join the roundtable. Thank you.

[section: "'Roundtable' with Wen-Hua Chen and Daniel Friedman"]

[editorNote: "2022 Robotics Symposium 1st Session ~ Part 6"]

[editorNote: "First 'Roundtable' portion of two"]

[sp: Friedman]

2:39:29 Well, welcome back everyone. So as it turns out, we may or may not have any people join, we will have just one join right now and then we'll see who else joins. And so anyone who's in the live chat please feel free to read any questions in the chat and we'll be looking at them. When what not sure who else will be joining us. So we'll talk about some of the previous presentations, not sure which ones you've seen. And otherwise, I'd like to pick up on a few threads in your presentation. And then we'll take any questions that people are asking, like, how does that sound?

[sp: Wen Hua Chen]

2:41:28 Awesome!

[sp: Friedman]

2:41:29 So one point that you highlighted was this notion of dual control, and how it brought you to some of the similar places that active inference has arrived at. So I'm curious what you think led to that, and what led to those vectors intersecting in a dual control and what is at that nexus or why does it exist that way and why is it coming clear to the forefront at this time?

[sp: Chen]

2:42:03 Thanks for this, that’s very interesting question. I think about it myself, from time to time, there are those two areas if your original was quite far away, we have different way to think about the world typically control, we normally we are interested in, as I said that the do control concept is not entirely new. And the people in the control community already realize that many years ago somehow like if you take any action, the action will not change their behavior of a dynamical system but also maybe you could have some influence on the variables you are interested in, in traditional control this could be, for a physical system there are some parameters useful like a mass or a damping or other things that you don't know, you by doing that will help you understand what you really are, just like when you're driving your car you have some rule where you know what I mess or inertia my car, have by doing some certain action, so that people realize that before but there's a difference now, because we can show you the move from typical, maybe we can talk about low level automation now move to higher level we call the intelligence autonomy.

Now, we move on to the pilot. So, then that means the dynamics is more an agent, away then we do the computer science or computer science ia an agent so, now, we more interesting not only about it, ourselves more interesting about the environment surrounding us the outside to my the work, there is more progress and what I did is more from your concern about your agents yourself, more about it what are the environment surrounding you, how they explore the environment, how to understand the your behavior in the environment. So, by doing this, I feel we bring the typical control in this type of a natural water, in this biological sense, because now you're more interested in how to deal with coexistence with the environment or the area. So this is why I view on this. But on the other side with this also what I read on the activity inference, but certainly this can vary. They have more say, if you're traditionally before that you control, people already have some idea about treating the human brain as a basic machine.

So now we said okay, I have a prior information about the environment. I have a new theory that can be helping you understand that what is happening around me about the environment, but what active inference for me I think about it, certainly the other one side how we define the reward function. I'm particularly talking about using free energy to quantify that, this really wonderful work. But also it is key things here is, about action, the action is also a link with my understanding of the environment about a perception. So the carbon, so using the action to explore the environment, it gives you a better understanding. So that it means that you move from th the human as a passive way to receive the information from the environment, now is that I can actively do something here for me to better understand why. So, I feel this way, this is my understanding, the quality is the key feature of active invariance. So, because this is really you can see the natural link with the control with all we talk about it, because the control over it talk about it, what is the consequence of your action? How do we take the best action? So, this is why, those two areas, they're quite different area created, because the leader for the research and also the something like a trend that has appeared, they are now moving together, in this particular area, the conversion to each other. So that's what I'm thinking about.

[sp: Friedman] Awesome, if I can pull out a few threads that I thought were really insightful there. So you cited a paper from the 70s, about this dual control notion, the idea that we had to have not a single imperative or have an imperative that contained epistemic and pragmatic components, and all that entails, the unknown consequences of action. So what we would have is like expected free energy, as opposed to the variational, free energy. And then you described how there was a movement from lower level automation control systems, the classical thermostat and other like, single variable, single fixed point implementations. And then, as the implementation complexity approaches the multijoint, and way beyond, how that multijoint is going to be in a social context or changing environment. That system that's being designed. It comes to convergently require the same imperatives of a nervous system, which is to say, like the real time integration of sparse sensory data. And also that is what authorizes the ecological stance and the embedded cognitive perspective, which ties in with some other recent threads in cognitive science and neuroscience, like the pragmatic turn. And so it really is interesting how,from the technical capacity side, the questions that were converged upon, in terms of memory and forgetting and all these things, the challenges that national systems have been involved in solving for a long time.

[sp: Chen]

That's also right. That's very interesting part of the technology develop, but also there is maybe demand from the society. And because of lots of traditional, mechanical or thermal, simple control, already wide existing, they help us to boost our productivity for many years. But now we reach to the stage that we want to further increase our productivity, increase our efficiency, and you have to have a highly automatic system, which is able to deal with some unexpected events or uncertainty. And so in order to have this capability, they also require a higher level of intelligence, like our human or animal. So this is actually another reason, technologically the move is because the society and economic demand for this thing to happen.

[sp: Friedman] Okay, I have another question about your scenarios that you explored. How is explorer exploit balanced automatically? How can such a large statement be made? And how is it balanced? When risk is in play? Like risk of going into a dangerous area? So within the search task, how is explore exploit mediated? And then how does that become more complex? Or how is it integrated in the model when bodily injury is on the table?

[sp: Chen]

Thanks for this. That's very interesting question. And also, we try to think about this a lot, ourself for a while. And the first I would like to say for the just using the autonomous search this particular examples to elucidate the key ideas, the fundamental objective for this particular task is very simple or clear, somehow, based on my understanding, I try to move origins, try to move close to real life, to real sources. So under them, they will formulate this as a reward, find your cost function somehow, like, you want to move out next time. So agent, the location to the source, locate as much as possible. But however, because you don't connect, so then you conditional on all the information, it connects so far. So this is the reward function, origin define it.

But from there, we derived this particular function, if the formulating in this way, and they also try to introduce the note about the action will affect our belief. And then we're naturally you found that the cost function, or the audit function become two terms, won't consider the two term, one term is about exploitation. Another term is about exploration. So there's a naturally happened, there is no near to introduce some terms, or they just naturally come together in this way. So we think that is the best way try to do that. But also you mention very good question about the risk, for example, if naturally you're not only something like a target that you want to follow. But also during the process, you need to be aware of risk there.

So normally, you have to deal with, in our framework in two ways. One way is that we have to add some constraints in our action generation, it means that, for example, one example is in our search, if there is an obstacle in some way, if you come on to your vehicles or aircraft move to that direction, suddenly this is risk, because the fly is going to comply with the obstacles, we added constraints in the search domain. It said in this area, he couldn't go, this is wrong way to do that. But also you can add a sum, we call the softer constraints that means in the cost function, you add some penalty in your cost function and said, okay, there is some area might have some risk, you try to avoid, if possible. And then when you generate or optimize your action, it's hard to take this into account.

[sp: Friedman] Alright, awesome. I want to connect that to active inference and then ask a great question from Dave. So you mentioned how various constraints can be provided to prevent situations of risk or hazard to the entity. And so that is what may work in practice. And so that's why it's been so interesting in the presentations to see that. Most of them have featured at the very least, laboratory Robot context. And that makes the full stack. Increases our confidence that the full stack, touches like there is test coil, there is a path through some implementation. And then the question is how deep in the specifics do you have to go versus how far up in the generalities. And then there might be some situations where the constraint is applied in a very situational way.

But also, as you laid out, dual control and reinforcement learning, you said, Reinforcement learning is not really amenable to being formalized analytically in practice. Whereas one active inference strategy that we've seen to balance a task performance with survival is you say, I want to reduce my surprise about the gas cloud. And I want to reduce surprise, and have a high battery percentage. So then it will balancing, explore, exploit within a drive to detect the gas or to stay high battery, it also can have a nested model that's balancing those drives. And so there's also analytically simple and first principles way to bring homeostasis and risk avoidance, into very generalized framings of the active inference framework. And then again, in the specifics, it might be useful to do different model variations closer to the edge. But then it's very interesting to think about what it looks like, when also there's something in the center. That has a simplicity to it.

[sp: Chen] Thanks for this useful discussion. Certainly, there are different ways we can deal with the balance between you want to do what you want to do, and also try to avoid any risk or pitfalls, and then try to balance, particularly the problem here, in my view is called uncertainty, because uncertainty will have an effect on other things. Because if you think about risk, how possible is this risk might be. So there is a lot of things like this, and come back to my fellowship, my fellowship was funded by EPSRC for five years, I consulted on this particular area, the goal of my fellowship is as we already somehow indicate, we try to increase the level of autonomy, by if there's more intelligence, I will into the control and an ASIC and a field. But one of the the idea for me is, we want to devise something, we call the goal oriented control system, which means we want to promote, because high level of intelligent people or animal, they are more have a goal oriented behavior.

Rather than just the people you said, I give you the goal each to figure out how to do it. If we have a nice intelligent, why is that I need to give you an instruction, every step about how to do things properly. So firstly is, the promote goal oriented behavior said Okay, for this particular, what is the task? What do we want to achieve? What's the requirement? So there are certain things that in the key, integrating my framework is about the constraints, the way the constraint is so important, because you try to avoid any Pitfall, any risk of things. Or, for example, if you want to develop autonomous driving cars, you have to follow the rules of the traffic road. And they have to follow that. And they have follow the traffic light and other things. And you don't want to comply with any other vehicles or hit any pedestrian. So those are the constraints you have, safety constraints in this case, but you also have a lot of physical constraints. Because if they have a maximum power, maximum temperature, or pressure your system could have, otherwise you're going to destroy yourself. So constraints play a very key role here. But there is a question there, how do you set it for different scenarios? How to abstract formula constraints is a question.

For any deviation or action you made, you have to respect those constraints. Before you try to think about well, that's a really meaningful objective. Another key part of this one is uncertainty. The uncertainty came from many ways. Could it be the environment changes or uncertainty we already talked about. But also could it be uncertain about your information, because you have a sensor, sensor could have error or your sensor range is not enough to pick up all the information you need. And also you answer their body your belief of the world, for example, we talk about that risk, but how reliable this risk would be. So I believe in the whole framework for do control. The key thing is about how the qualifiers uncertainty, about your belief of the surrounding environment, this is driving you, you reward it somehow like an exploration. So, those are the key things in my view.

And basically, if one of our idea listed here is about, you talk about in the active inference, we are able to formulate that in an analytical way. And the MFI formulating analytical way, we are able to using some tools or theory, people are developing in the last 30 or 50 years in particular the control community and other community were able to form or approve, if we do it this way, we can make sure you are able to satisfy certain safety requirement, it will not hit you that some obstacles, you're not putting yourself in the danger, for example, in the natural world either by all animals, for example. So, this is the dream, we have some progress in this area, we are able to do some very simple system, we are able to prove stability or safety of that you control. But however we want to do is try to extend to a much wider world. And therefore, the free energy principle is much more difficult because energy at the function level is quite a complicated, how to understand that that is that another level of difficulty. But however, in principle, we are able to work together to push this.

[sp: Friedman] Thank you there was really a lot in there. I'd like to make one remark on active inference, and then bridge to quote Dave's question in the chat. So you highlighted uncertainty. And that's of course, a core aspects of active inference with bounding surprise, using free energy. And then you mentioned goals and constraints. And that really seemed to me like a common point with cybernetics and goal orientation and constraints, General Systems Theory, cybernetics branch, but also engineering and entrepreneurship and innovation, as your colleague Steven Fox has worked on, and those perspectives on goals and constraints of potentially nested systems of organization, like projects within an organization, or a firm within a market, or a cyber physical system nested within a firm, within a market, to have interfaces that can even be described in an information partitioned way. And then you brought it back to safety and to be able to have certain probabilistic or formal guarantees on those arbitrarily composed systems, is very exciting direction. Any remarks on that? Or I'll ask the question from Dave.

[sp: Chen]

Just to have a quick remark. It's really more for me, I'm more on the technology side. But however, it is absolute right. This goal oriented behavior you can using for the social organization, using for the biological or many other things. Because basically, when we survive, we have a goal, this goal, we try to survive on the food, and then a new organization, the goal is to try to find a more profit, constrained by the marketing environment and many other things. I absolutely agree with you.

[sp: Friedman] I'm just going to make one more comment to refer back to an earlier talk. Not sure if you saw this one. But this was Tim Verbelen talk. And he was talking about video games, and about how with a only a epistemic drive, some of these video games were able to be played very well, like with pong and with Mario. And then it made me think about how in a lot of video games, staying alive is an imperative, whether you're typing something or a maze, or it's something that's growing or shrinking, it's like staying alive, bridges the gap between search and exploit, and all these different behavioral modes. If you're not staying alive, if there's no idle process for CPU that it's over. So then there's no point in future epochs. So that's really interesting. So let me go to Dave's question. So Dave, wrote, Professor Chen, I didn't notice discussion in your presentation of, effect, or emotion or drive. What do you think about adding such mechanisms to the dual control model? Could this amount to explicating internally generated motivations? Or was such a trick be a mere disguise for inserting arbitrary experimenter's specified rewards?

[sp: Chen]

That's a very interesting question. And while I am reading the literature, in active inference, and there I'm fully aware that the focus of our research is quite at low level, we focus on to something specific or useful. And in this case, our focus is on the autonomous search, trying to find the location of resources. And the PV form, generally, the renewable energy object is quite a simple set, we want to harvest as much energy as possible given the condition. So that's why the focus of our work is very specific. But however, when we come to the biological and also human and others, they have a lot of things like the emotion and the many other things we did consider in to in our current work. And I can see this is the gap between dual control and the active inference is, actually you can deal with that in a more general skills like a human power, or confidence, or some other emotional things. And this is actually the direction of maybe the future of our work, should move, try to learn from this community about that. But in principle, and as I said, we were able to formulate those emotional and many other things as reward function, for example, you you, encourage your people to be happy. But you need to have some way to quantify that, if we couldn't capture that, maybe you were not promoted behavior, try to make you happier. So that in the key things for us is how to formulate interesting reward function. And this is also what we can learn from active inference principle, and we didn't have a restriction on what time, what type of reward function should it be? What type of constraints should it be? The framework is quite general. But however, for more complicated systems theory, there is lots of the work. That's very interesting.

[sp: Friedman] If I can build on that, so I was imagining the setting of firefighters, and there's some different chemicals that are being sensed, and about the way that the extended cognition paradigm, and seeing the cyber physical team, as being just qualitatively, whatever tools are using, even if it's just the walkie talkie, and their bodies, it's still an extended cyber physical team. And then, as we move forward into futures, that may, in different areas, include all of the tools that we do and don't know about. So then that's what's interesting about a framework that can start and pick up in the, qualitative zone, and then also take it all the way to the application. And then as to value alignment, I thought that what added had some seeds of new ways to think about the human robot, or more generally, the multi entity alignment question. And that is their preference vectors, or some of their preference vectors could be about the same thing. And in the same direction, like the semantics of what the firefighter on the survey says, I want to like balance x and y and z in this ratio. And then there can be an entity, whether that's another person, or some explicitly structured cyber physical entity that also has that same preference distribution. And that is a formal way to find that probabilistic alignment, because the question has to be addressed one way or the other. And how will those distributions align accidentally? Or using some other simple heuristic?

[sp: Chen] That's absolutely right. That is actually when we talk with our end user and also fire fighters. And also the minister of defense, they're interested in the terrorist attack or some other things in London in the tube station, there's some scenario like this, and here they are talking about is very rarely, just send a robot out. And let it do off to the thing, is actually is always have an interaction between as a first responder and a robot really want to pass the information about, well, I thought it might be. And at the end of the day, the person who does want to provide some extra information, and they always work together as a team, and also there are some preferences. For example, in some areas based on that first responders experience they knew where they are more likely couldn't be, there when they see a picture or see the season. So there is always the interaction that you have. So this is actually our future staffing, is somehow likely to promote this interaction between human and data, in some preference on many other emotional or urgent things because some area. It you close to somebody exit or somebody maybe have a priority to search or find whether there's some problem there.

[sp: Friedman] Few remarks on that. So it made me think about how the response network, like an emergency could be seen as embodying a prior, like where I am in California, maybe firefights are a certain likelihood, different seasons. So then a phone call to emergency services might have a different likelihood of something being the case in one region versus another. Or it can be used in a Bayesian filtering way, where are we getting 15 reports of the same thing. And then where we're already working on that situation. And there's something else that needs attention to be brought to it. So we don't want to like have a sampling bias. And then that question of how training data in a static learning context results in basically, like biased implementations in the real world was the theme of several of the talks. A question I wanted to ask was about the turbulence of the flow. It brings a chaotic, multi peak landscape, because what I saw in the cloud was, it's like island chain. It's not one ridge. And so how does a smooth Gaussian variational approximation make sense of something that otherwise we might think we might use complex?

[sp: Wen Hua Chen]

3:09:54 That's a really good question. And we struggled with this for quite a while, and you can think about it that you have a lot of local turbulence is there and also coupled, in any case, if you have a chemical barrier to dispersing the concentration to the AI is actually really low. And also for our UAV, the small drones or the robot, the sensors they carry is not very advanced, you can't carry some labor grade, very comprehensive equipment, is actually we use a very simple guess sensor. So that means that you have a higher level of risk detection and also what makes it even worse is that the turbulence you can make. And when we operate on the UAV. The propeller didn't help us, itself, it generated the lots of local fluid it upset our sensor, so its hard now, it's somewhat appreciated lots of hard work and getting into this area. But as I tried to answer your question is when we recently, we couldn't use a more complicated model. But however, the company can't afford or sometimes in this case didn't give us too much benefit for two reasons.

One really is the complicated model is always have high level of uncertainty and even you have a company code model, is accuracy to the present a real environment, then that's configure more or give you benefit, if the model environment is so much uncertainty there, maybe the simple good enough model is able to do the job, is the first question, but it also by union simple model, it can significant driving you are a computational fluid down, the simple Gaussian model it is very simple.

3:11:49 But however you are able to drive in you computational fluid down because it come here with a CFD model, computational fluid dynamics for the oboe complicated model. Secondly, is it because of the particular scenario, the sensor is not high grade. So a lot of onsen they caused by model, or maybe just the display within the sensor noise. Because noise is quite high even you try to push it more and more and more accurately, but it's just maybe 1% since the sensor gives you 5%. So it didn't give you too much benefit. This is what we have on this situation.

[sp: Friedman]

3:12:25 So I'd like to maybe connect that gas dissipating setting to one of the earlier talks. And again, not sure if you saw it, but to recapitulate the point. So this was from Tim Schneider talk. And Tim spoke about goal driven active exploration. So I'm sure that there would be a lot of resonance there with dual model. And one of the questions that he really highlighted was, he asked, "Can the familiar have intrinsic value"? Because he described this problem called the detachment problem. Where a region of high posterior likelihood, a good region to be in, is getting walled off by, a well explored region. And so that dissuades further epistemic ly driven actions into that ring. It's almost like we've already been there. But then it's like, the new finding was, one more paper down that got done that bridge. And then we talk a lot in active inference about morphological computation and embody computation. And in the setting of the gas dissipating, there's several ways, we can be really specific when we're talking about applied embodied computation. So one what you just mentioned, with the UAVs, and the fans, and how that was causing distortion. It wasn't like a free floating sensor. And that's like our own body models. And so people talk about how the body is a model, and it has a model of itself in space. And that's how we can do all these actions. And then the second example of, embodied and extended cognition was the way that the gas was dissipating. So it's almost like the forgetting in the model was happening automatically. Because you couldn't build up a heat map of where of, the integral of gas flowing through a region at a time, you have to have something that is dynamic, but you're local, searching a space. And so your estimate in other areas that are distal, will become increasingly uncertain. So what does that make you think about in terms of the work that you're doing?

[sp: Chen]

All those things are very interesting. There are many direction for that. And we think about it, the work we're doing here is just trying to illustrate a very basic principle about how to take advantage of the action you take to give you the new information, and then from there to help you. So this is basically as we talk about a bit, that same spirit as active inference. So this is a fundamental things, under in terms of scenario and given the complexity. There are many layers we can add other things on. And also one thing you mentioned about, for example, the influence of the agents or a robot is dynamics, but also could it be, for example, we consider a source now is in the stationary, is fixed, they just released the gas. But in real life, maybe there is a move aisle and things there. People are some terrorists, for example, putting something on the other track or something they're driving around or some other things couldn't happen. And they also talk people talk about intermittent release some time release, and stop and then release again.

So there are many, much more complicated scenarios here. And could be very interesting, coupled with some other things people talk about. For example, you couldn't have more than one sources release, it's not a single source, we have more than one. And also people talk about if you have a large area, if you have a number of agency try to work together. Now we talk about a collaboration between the different agents and how they work together more efficiently to search the area. So there are many things here. And one particular thing that I feel is directly can get from the help from your community is, now we only look at one step ahead. But then you realize, we already have some similarly, if we look at five step ahead, exactly give us a much better result, because you're looking further after the influence of those changes. But however, the downside is, we already talked about it is about a computational load. So now you have like a CI search. Because each step we have a number of directs, you want to move your agents. And if a many multiple steps, and the combination, it could be quite nasty. And we now have a researcher tried to think about, the Monte Carlo Search or similar car also provide of reasoning, provide some idea about your work in that area? How can we embed it into our work to take advantage of this? So there are lots of interesting things here.

[sp: Friedman]

Awesome, I'd like to create a few of these points of contact, pick up where you said that you're planning one step ahead. Which is analogous to the variational free energy. It's the instantaneous best action. And then the expected free energy takes you into the future. And I wanted to mention a few different ways that temporal planning is accomplished. And some were mentioned in the earlier presentations. Also, it's interesting to note that, however, many years ago, I don't know the exact number. But somewhere in the 10 years ago, range, active inference was like an instantaneous perception, cognition action theory. And several elaborations have specifically enabled it to account for increasingly distal planning.

So one example is like in the continuous time setting, having a Taylor series approximation, of the generalized coordinates of higher and higher approximation depth, is one approach. Another approach that can happen in discrete time, is having a broader time horizon for policies, as well as with different tree pruning approaches. Another approach that can work with discrete time or with hybrid models with discrete and continuous time is hierarchical modeling. And so it's very interesting to wonder whether for planning 100 steps out, to think really deep into how the UAV will do something far away. How does it chunk that? And how does that chunking into is it 100 step? Inside, the way that it starts to chunk and understands, are the ways in which the computational burden is reduced. And also those ways that start to resemble the ways in which biological cognitive entities also make sense of their environments?

[sp: Chen]

That's absolutely right. That's a very good way to move forward. We also doing some thinking this way, but not necessarily coming from the same direction, because we think about it for example, when you make a decision on using the autonomous search problem, you somehow try to design your waypoint, where you want to go to that. And suddenly you have a question about how far the step size, this is actually can change. And even the large area maybe want to move a little bit longer distance. So somehow you can regard this as heretical strategy. And let me actually give you the combined a two level UAV, control autopilot, they try to follow those things. So there are lots of things that we need to think about, somehow like his trade off between performance, computation load, and the horizon you are looking at, in theory for longer, you give you a better performance, but however, how far you're able to looking at. So there is a trade off between those terms, maybe for different applications are going to have different factors. But the whole idea, that’s quite an interesting, is actually worth to explore.

[sp: Friedman]

We have also to pick up on some similarities and differences with the presentations. Some of them utilized neural networks as modules in their training, other used variational Bayesian methods, which can be fit it as an optimization problem, and also we saw sampling based approaches. So pretty broadly, how do you see these different ways of doing robotics and edge computing? How do you see them working in different situations or together with pre-trained or updatable models that are large or variational or sampling based approaches?

[sp: Chen]

That's a very interesting topic. It's quite a broad and there are lots of research nowadays, about using pre training in the model and particularly in the context of reinforcement learning, for example, if you learn things and then try to deploy them, either in the real life or in particular situation for the robotics, as well, they have lots of research in the area. And for me, I didn't have time to expand, advocated those ideas fully, but I think about it as lots of problems whether it's engineering system robotics or the biological or the human is however, the city could it be described like in how to make optimization at anytime, the optimal decision could be in terms of trying to find a food or try to be survive or try to do something useful, so all these problems in my view, it can be summarized as a optimization making problem. And for this one, even when you have all the environment information known and also all the behavior for your agents unknown is not easy, but whenever you try to deal with something like what we talked about is uncertainty in the environment, and the environment will become much more challenging.

So, there may be new single solution for this, this why he talked about it, and many different approaches they tried to deal with the problem, for me is there are two major approaches, I'm thinking about it one way is the iteration process, that iterative process is particularly like in the reinforcement learning, means you have some initial strategy, you try to take the action from the environment reward functions, there are steady change, you learn from that gradient somehow you make your policy or very function clues to truly the optimal policy. So, you're always doing that in the iteration learning. So, this is a approach and because this approach, you need lots of data, this is why now people tend to train in strategy beforehand, and then deploy that and maybe online he can adapt to a little bit of to that, but if you using an offline training, using alots data to take advantage. But there is another approach more in Active inference or dual control, I call it as a purely online optimization approach. The unlike optimization process, said okay, given all the scenario, given all the information I have with about the environment, given what is my objective, I try to work out what is the best study I should have, given all the information I have, on the body environment about is my reward function, I try to work out what are the best strategy. So then this problem, can formulate as an online optimization problem, you try to set Okay, given all the information connect so far, given all the understanding, you tried to do that. And for this approach, you need to have a larger computational load. Normally, as you talk about aging computing, and this is why we struggle with talk about it one step ahead, because one step ahead is being used as an optimization problem either to solve, if you look at both of us, they had the optimization problem couldn't get him much more complicated. And aging computing maybe not good enough try to do it. But in principle I regard itself as too broad approach to that in the active inference. This is precisely you try to using free energy or expected free energy as a reward function, you try to optimize, your action to give you the best possible one. So this is why, I feel is this similar approach that we'll talk about.

[sp: Friedman]

So while you spoke to the dual control systems, thinking about how it might have formal differences from free energy principle and active inference as we know it today, or again, we discussed earlier how it might have reached some of the same points from two different angles. And it may be think about the particular partition, and the Michael Blanken or the Friston Blanken. So, do you have any thoughts on this, or I can provide any more context, but first, I wanted to ask you, if the concept of blankets was relevant, or there was some analog in the control literature, from your perspective?

[sp: Chen]

Maybe we can say we always do that in our control community. So, we always do that, in the sense traditional where we look at control is our own dynamics, self. And in the sense, I try to pick up the information, then the action we take. So, this is a control where is the sensor and then your own thing and then how you act, however, previously control we very much like, ignore the interaction with too much about the environment, we talked about environment in the control, typically, we call that disturbance. So the aim of our control system when we are existing, is try to act against any disturbance, because we try to produce something ourself, or a keeping it for example, if you think on the keeping your room temperature at a 30 degree, if some one open the door, is a new temperature in the room, if the external temperature change, there is our control is somehow like, I do care about anything outside, I care about these sensors take the information or do something under them, I take the action. So it is always regarded the water is information from the sensor, and we take the action, which will have some influence outside, then we take the information from the sensor. So when Michael Blanken, I found that there is a natural, and maybe somebody with some thinking we have Ipoh, this is quite an interesting way to look.

Because in this way you don't care about someone open the door, don't open the door, you don't know, because he said from the sensor, what's the temperature changes, and we take this ignore anything outside.

[sp: Friedman]

I'm glad you added that, because I also had wondered whether the control loop was pre Active Partition, I mean, input output system, systems with interfaces, holographic systems, more and more equivalences have been found. But it's the sparse representation of interaction between two agents or with an agent in a niche is like, well, you need the road going one way, and you need the road going the other way. Otherwise, it's not, you haven't closed the loop. So you have those four pieces, like the two entities in the edges. And then it is interesting with the way that what comes from the environment is described, is it a perturbation or disturbance, something that should be controlled, or, as the case with allostasis and like biological processes that are anticipatory, and then going all the way into novelty, which is the ultimate anticipation. It's the anticipation of the different. And then it's again, paralleling the development of industrial control systems going from stabilizing vibration, into needing to be proactive. There's also again, a natural coming together, as the attention to these fields, turns to finding formal cognitive models. Yeah, you're absolutely right. I think that the principle of the micro break.

[sp: Chen]

It is interesting, and relevant. And the big difference from traditional and uranic culture thinking to what are thinking in your area, or current, our thinking is about how to present the environment in your brain. So how you try to say, “This is that make whole thing different.” As I said previously, you don’t care too much everything like today. The disturbance are just interesting that your heating system and other and now is actually a, no, I want to have some way, if you want to anticipate something happened, it may have a better representation about the environment. And also you want to align your beliefs or insights state working also on external state, so that is where the things comes in, and also where you're able to make some high level division, make where the intelligence come from, because you have better representation about that. You can figure out a better way how to do it, and then how to get anything from the environment.

[sp: Friedman]

So one example that made me think of and also connecting back to the embodied intelligence in the morphological computing, I remember seeing a robot or a little vehicle. And it was able to move over a surface that looked like a stair on its side, it was very jagged. But the wheel that this machine had, was shaped like a square that was the right radius. So basically, it was able to roll perfectly, smoothly across that one frequency of stare. But a different frequency of stare, it would have been a total bumpy ride. So if the wheel would have been small, then there would have been a debate around, well, should we represent chunks of stairs and up and downhill and all that fine scale. But then when the morphology is fit to the niche, in a way that's natural, or in a way that is off sourcing some of the computation to the physicality, then that entity only needs to consider like a linear movement as if it was like in a simpler space. And so then it's almost interesting to ask, like, in some of the presentations, they used, very standardized robotics platforms, the quadcopter, and the turtle bot, and other standard, to the extent I understand standardized robotic hardware, which is awesome, because it increases accessibility, and it demonstrates it in a clearer way, like tomorrow, we'll hear from Legos, implementations, and so on. But then that element of embodied computation, starts to show how we can almost work in a different way, and ask what systems could implement certain functions, maybe there are shapes of robots or other objects, we haven't seen the shape yet. They don't have to have two legs, they don't need to be five feet tall. They don't need to look like a trash can. That's some of the morphologies. But then with the air, and the water and the ground, there's so many bodies, insects. So it's going to be really amazing to see how this is used proactively to design morphologies and behaviors that do things we haven't seen.

[sp: Chen]

You're absolutely right. Maybe people call i the fitness slide, somehow like this, and is actually somehow you can use free energy or some other notion to describe because you live in an environment, you want to get the best out of that. And we talk about it now is a strategy, how to do it or how to think. But however, is the natural world, because you basically are happy there, your things are gradually involved with you. And if we are in our design, we can choose those physical body always as options as something we are able to change it. And maybe gradually can combine those two things together, it's not only planning to make the best strategy, but also maybe called the actuators or your physical bodies, all the things you are graded, will change it with that. So this is about how you set up the problem.

But what I feel much more interesting is in the activity inference, when we are using free energy, and then you can try to capture much broader behavior. And as I said, in the control area, we now is a maybe more focused on the specific task, specific mission. This is what we do, physically want to do it. But however, a lot of things like softer skills and like a more broadly about it, like our competence or capability, we don't talk about it but a human, when we do the things we learn, Learn, Build after the confidence or embody our skills, and then we do more things. Now this is things happening and active inferences are able to explain that they able to have a two framework to do this. We are maybe more at the physical Alliance. So I can see things that Granger can move it together, and you make robots, for example, more capable to do something, if they have the ability of changing the borders or changing the actuation, changes other things, or even maybe there have come up with improving in sensing because there's something greater they learned and found a boiling point of them either sensing particular environment, they were trying more develop that particular sensory capability. So I can see that naturally. But the question is about how to set up the problem. We allowed it to make this happen.

[sp: Friedman]

Well, one freaking day that reminded me of from my own area of insect behavioral modeling, is there are many models of task performance, like digging or foraging. However, there are fewer models that are describing tasks transitions, even though those are really important for the colony. And then the models of task transitions tend to be more generalized, dynamical, simulations and less getting into the agent based modeling perspective. And so as we're seeing robotics, with the physicality, and a technology pushing the frontier, that type of task switching becomes important higher and higher orders. And then again, that brings us into the bio inspired design conversation, because task switching is so essential. And the idea that, the human is this unfolding of memory, and anticipation and all of these different features. And it's hard, functionally or neuro anatomically to separate out how the human brain works and how animal nervous systems work.

And so that'll be another interesting area with this tension between explainability and potentially even austerity of the models, in that they'll have parameters, but the parameters in the way they interact, even for a few parameters model, might be difficult to understand, because it's not like going to be all the information is in those generative model parameters, it's going to be those model parameters, and the dynamics of how gas is in the world that are relied upon, outside of the focus, the background context for the model. So the model itself won't be fully understandable or explainable because it's going to rely on this context, just as no sentence can stand alone. So there's so many interesting areas and to see the directions that different fields can meet at and then start to structure a productive relationship.

[sp: Chen]

I also obviously agree with you is about the importance of models, in many ways very important for us, I knew that in the machine learning area, they have a model based approach and a model free approach, I am more biased to model based approach, because you can use a a model free approach, they are quite a powerful in some ways, but however, maybe they suffer some issues, you already highlight, how to explain this? Why make this configuration? Why take these actions, and more explainable and furthermore the best one because lots of things that we are doing and particularly in our area, they are engineering systems, they have a first principle or other models already there for many years, but however is now the question is about how to make use of that. And so I prefer model based approach in many ways. One is for the explanation, try to either understand the action, but also for somebody efficiency, somehow like a you can use less data, because you have a model based approach and in our engineering award that data means money. And I knew a lot of people say okay that Googles and Facebook can harvest billions of data online, it will freely but however, in the engineering if we want to do something, if you the experiment, to test, if you're into physical wrong into something to get the useful data come out from that. So that is I mean, the money. So when we're using the Model S, of course, is much more efficient in terms of learning, understanding, what's happening around the environment. So this is why economically, I feel is quite important for this, not only for the safety or making the more expendable. But there are some other reasons.

[sp: Friedman]

Well, very interesting. Is there any other remarks you'd like to add or questions you'd like to raise?

[sp: Chen]

3:40:37 Not really, that's a really a very good conversation. I'm very pleased as part of this community, as I say, and it's a surprise for me, and the people share the same idea. So what I'm interested in is getting more involved in the public community. And also I would like to open the door for anyone working in this community. They want to talk with us, we'll get together, and the diversity, the ideas, as we already discussed, and they more than welcome, and it could have my contact under the chat, to talk with me. And so basically we share a lot for fundamental ideas and we can also see that there are some different tools, different slightly, different concept and approach. If we are able to work in together, I will think about it, we make it not only as a tool to try to integrate, how the natural world and the human or animal their behavior, like how they, but also make it them as a useful tool, to drive out to this theme for desire more capable robotics, and do something for the society.

[sp: Friedman]

3:41:44 Amazing, great. What a great discussion, big appreciation to Professor Chen for joining for that. Well, that concludes the first interval of the second applied active inference Symposium on July 31. At least it is now where I am. And in about eight hours, we're going to have the second interval. It will feature presentations by Bruno Lara, Matt Brown, Adam Saffron and Jeff Cloudier. It should be a great set of presentations, followed by a roundtable discussion featuring several of those presenters as well as Karl Friston. So, hope everybody has a good break in the eight hours before the second interval and prepare some thoughts and questions and writes them in the live chat or emails us really appreciate you, spending the time and attention listening to this active inference Institute symposium and hope that you'll stay involved participate and keep on adding, so goodbye everyone and see you in the second interval.

Symposium Part 2

Transcription Details:

File Type: YouTube Video
Length: 4 hours, 00 minutes, 18 seconds
File Name: 2nd Applied Active Inference Symposium on "Robotics" ~ 2nd session
Transcription Type: Non-Verbatim

Speakers List along Topics:

1:48 Bruno Lara
Presentation Topic: Prediction error dynamics: a proof of concept implementation

32:44 Matt Brown
Presentation Topic: Real-time Robotic Control through Embodied Homeostatic Feedback

1:05:44 Adam Safron
Presentation Topic: Generalized Simultaneous Localization and Mapping (G-SLAM) as unification framework for natural and artificial intelligences

1:42:12 JF Cloutier
Presentation Topic: Towards a symbolic implementation of Active Inference for Lego robots

2:23:13 Roundtable with Jakub Smekal, Bruno Lara, Adam Safron, JF Cloutier, Karl Friston

2nd Applied Active Inference Symposium on "Robotics" – 2nd Session

Daniel Friedman: Welcome back to the 2nd Applied Active Inference symposium. It is the second interval, and it's July 31st 2022. In this second session, we are going to first feature a presentation by **Bruno Lara**, **"Prediction Aerodynamics, a proof of concept**

implementation". Following that, we'll hear from **Matt Brown** with the presentation **"Real Time Robotic Control through Embodied Homeostatic Feedback".** The third presentation will be by **Adam Safron** on **"Generalized Simultaneous Localization and Mapping (G-SLM) as a Unification Framework for Natural and Artificial Intelligence".** And the final presentation will be by **JF Cloutier Cloutier, "Towards a Symbolic Implementation of Active Inference for Lego Robots".** We'll then have some of those presenters rejoin us in the final two or so hours of this interval for a roundtable discussion. We'll also be joined by Karl Friston in there. So thanks, everyone, for watching live or in replay, hope that you add any comments if you'd like into the live chat. And otherwise, thanks to all of our presenters and co organizers for their awesome work. And thanks so much for joining Bruno, please take it away.

PRESENTATION TOPIC: "Prediction Aerodynamics, a proof of concept implementation"

Bruno Lara: Thanks a lot for the invitation. I was very surprised, as most of our work is not actually active inference off course, it's related. But since we published a couple of years ago, a paper that actually I'm presenting a bit of these results here. Well, lots of nice and interesting people started to look into this, implementation of prediction error dynamics. And it's actually the part that we're taking out of all this framework to try to implement in our robots agents. For I don't know how much or how many times you've heard this story of why we are doing this cognitive robotics, or why we like to call all this research or this area, as cognitive robotics, and like a lot this slide, which it's usually a long introduction on the history of artificial intelligence and robotics. And it just tells, this story of 50 years of research trying to figure out how can we have machines that are as intelligent as humans, and it comes out that actually this upper part of the image, quite good results rather fast. We cannot say easily but it was more or less fast. And then we have the second part of this the bottom part, which is what comes out to be the most difficult challenge for robotics.

So it has to do with interaction with the world, you have a small child that is capable of handling these objects in the environment. And then you have this other robot that can do it, but at the moment that you change the size, the weight, the position, wherever you want of the pieces or of the chessboard, you actually have a child that with no problem can adapt himself to the challenge. And on the other side you have another PhD that has to solve it if you do the same for the robot. So in reality, what was supposed to or was thought to be the hard problem, which was having a robot reason and solve problems. It came out to be quite not so difficult to solve tasks, and we can talk about more difficult challenges that have already been passed, such as playing Go, which is way harder then chess, and we have AlphaGo a couple of years ago, while winning against the human champion. So we like to think that we are doing now, things differently. We're having robots that interact with the world, that interact with what's going on around. And they learn through this interaction. And of course, that keeps us lots of challenges and lots of things that we have to solve. So you could think now as an all the school of internal models we work in this field for quite already some years. And this part of the world where there is inverse and forward models for control, of course, and they are thought to be behind all these important issues in humans.

And since the beginning of my career, we've been doing implementations of different types of tools for these robots, but always based on these inverse and forward models. So just just a quick reminder, for those that might not be very much into this type of models. So we have a sensory situation, whichever it is, whatever it is, and we have our desired sensory situation, we have an inverse model that takes as input those two things, the sensory situation at time t, of course, the sensory situation at time t plus one, which is the result, and the inverse model is going to tell us what's the motor command that needs to be performed to go from here to here, and then we have a forward model that takes the sensory situation at time t and the motor command at time t, and gives us the prediction of what's going to happen with this sensory situation. And so, we have a prediction error, we have lots of errors, but we are interested on particularly this error, which is the difference between what we actually predicted and what happened in the world. So we've been doing this for quite a while.

Well, we've also use this prediction back as a sensory situation. And we can get long term predictions, but we can do lots of comparisons between what we wanted and what actually happened and lots of different errors, but as you know, and well now everyone works with is actually this error, like the difference between the world and what actually I predicted. That's what we can say we have in common, well, some years ago, actually, we came across all these ideas of prediction, predictive processing. And we started to dig into it to see what actually we could use for our models, what could be useful for improving our models and our agents behaviors. And we have lots of doubts, lots of questions. But one of the first things that we've done so far is to look into what happens with the error as an agent is executing an action. But first, I'd like you to walk you through one of our implementations first, where is the cross areas of what we believe, it's important in this case, we have active inference and prediction error minimization. So most of us are very familiar with this representation of what's happening actually, during action. And we actually believe that minimizing prediction error is what leads to belief updating. So, like the change in a prior belief encoded as a posterior belief, and this is actually informational gain. So this means learning. So, inactive inference, the expected futures, these states are fulfilled, through action execution, we know and this associated expected prediction error is minimized by actively sampling sensory information. So an important part for us is, this expected prediction error. And we believe the attribute of a policy, which can be epistemic and instrumental, in case this action is novelty searching, it's reflecting its epistemic affordance. And we could say it's acting for information. In case of preference searching, now, this reflects instrumental affordances.

And its action for reward. So in words of Kirbenstein we can think of active inference as the process of selecting relevant affordances. So those which are expected to minimize prediction error in a context sensitive manner. So what we've done actually, or what we wanted to actually implement, is the, how these expectations about the dynamics of the error cause or are related to this embodied feelings, and we believe they allow us sensitivity. So how well or how bad an agent is doing at improving the grip on what is relevant, in the landscape of affordances. So the sensitivity to changes in the rate of prediction error reduction is what we call prediction aerodynamics. And we can say the steeper the slope, the faster the rate of reduction, and we see some some examples, very simple.

So in black, we could see the actual error as the action is executing. And then we have a slope associated to this error. So what we don't want, what the agent doesn't want is, this error increasing having a positive slope. And on the other hand, there is decreasing then we have this slope, and this is actually what we are looking for. So prediction errors are manifested as changes on effect. So if the rate of prediction error is faster than expected, we have a positive balance. And we have an action policy, which is more precise. In the case that the error is lower than expected, or is increasing unexpectedly, we have a negative valence an action policy, which is less precise. So walking you through a couple of implementations that we have done. The first one is an example of of this mix that we're trying to have. The error is used for learning, but we have a very simple implementation of self organizing maps, we call it the self organized internal models architecture. The nice thing on this architecture is that it actually doesn't have to have an inverse model. What we have is a self-organizing map that organizes the motor sensory information. And on the other hand, we have a visual sensory information which is also organized in another self-organizing map, and then we have what we call a multimodal representation. And in this multimodal representation, we have associations, we have associations between a sensory situation, another sensory situation, and a motor command. So you could think of this as an inverse for our model pair, but it's actually not encoded as such. So we have associations between sensory situations and motor commands. And so we thought this was very interesting and we use it, for example, for saccadic control. So the robot has some initial sensory situation, which is the stimulus somewhere in its field of view. And what we need or what the robot wants is to formulate the stimulus. So this is the sensory situation, the desired one. And we ask this self organizing maps architecture, what we need to do, so to bring the stimulus from here to here, and it's executed, it's not very precise, so it comes close to the center of the image. And then we use this as the new sensory situation, then we have the same target, we again, ask the architecture, what do we need to do, and then it comes very close. So after 100 rounds, you can see the robot, this is the starting situation. In red, we have the first prediction and execution.

And in green, we have the second prediction and execution. So it's a very nice simple architecture that actually works, as I said before, works like a forward model. But it can also work as an inverse model. We use prediction error to learn. And so we could use it as some modular architecture, we can put more maps. In this case, we have the position of the head, visual stimulus, the position of the arm. And what the robot can actually do is, find the stimulus somewhere in the space, and then bring it to the center, of the obviate it and then actually bring the arm also there. So we have all these associations between movements of the head, movements of the arm, movements of the eyes, and all these get associated, are coded as initial and ending positions. So the next question, or the next thing we tried to do was, how can we use prediction error dynamics to guide learning and this paper we presented a couple of years ago in Epi Rob? It was actually Guido Schillaci that presented it, which is our co author.

So it's a work what am I given, I'll handle Assyria, which is also a colleague and myself. And what we did there is. I won't tell you much about the mats or the networks that were used in detail. The important part is what we see here. So we have a very simple robot, this is what you could see here, it's up to two degrees of freedom, camera mounted on artificial field, where we have lots of plants, and the robot moves towards a specific destination. So it wants to look at some image at some plant. And for each movement, we have a prediction error here. So we organize the goals in a sum, are encoded using an auto encoder. We use the middle part of the encoder to have represented the goals here. And the important part is each one of these goals has some prediction error dynamics. And so we go back again to our inverse model, and forward model, and execute the command, the motor command, and we do our prediction, and we get an error between what we wanted. And what happened. Then interesting part and what became nice, and what we wanted to implement, what we were thinking about this, we append this prediction error to a buffer, and this buffer. Once that it contains more than four predictions. We do our linear regression and actually what we get this an indicator of the progress. How good are we doing? So it's a tendency for learning. So, when we have a negative slope, it actually means we are going towards the goal, we are doing fine. So, progress is increasing, it means there is a positive emotion and we will remain on this goal. So, learning is going fine when the slope is positive, so, the activities are away from the goal, there is no progress, there are keeps increasing. So we have what we could see as a negative emotion. And something that can be encourages them to switch goal. So, we have a positive slope means increase the size of the prediction error dynamics buffer.

That was something interesting, and I'm very new in this field, in this area. We haven't thought about it before. And what we actually did is, okay, what happens if my slope is positive, it means I'm doing very bad at this task. And what I'm going to do is, I'm going to increase the size of this buffer. When we have a negative slope, it means, I'm doing fine. So I'm going to decrease the size of this buffer. So what we're actually doing is adjusting dynamically the size of this monitoring window. And we're doing that depending on how things are going, with respect to what we're actually expecting. So if the prediction error increases, we have a positive slope and we do a more frequent evaluation of the feedback. This allows a quick correction of the action and it can lead to satisfaction, in case we managed to do it better and induces abandoning the goal. So in this case, after a number of iterations, interactions, where the error is not decreasing, they are keeps increasing, then we can change, we can switch goals. And we could say we are trying to avoid frustration.

So through intrinsic motivation, when we try is search for a new goal. When the prediction error decreases, we have a negative slope, we don't need to be evaluating the feedback so frequently, and we can free resources for the agent to do something else. There is no more prediction error. So that means we've achieved our goal. So learning happened, learning occur. Again, we search for a new goal now. So when we select a new goal, we give priority to those that have a negative slope, which is steep in the prediction error dynamics. And we have some examples here of how the error moves. As we are moving in the world, and how the buffer size increases when the error increases, and then it decreases. How when the slope, now a game changes. So that was one of the first things we did. And now actually Adam invited us to this special issue that he did in frontiers. And we published their paper, which is actually well, at the beginning, it was about something else. And then we ended up with presenting this model. This is just an idea that we have, which actually encloses this part that I talked about the slopes, and the expected error. So what we are suggesting here is that. So we have an agent that has maybe physiological needs, in case the agent doesn't have physiological needs through intrinsic motivation. We want to do something new, we want to do search around the world. Then we go to what we call the environmental context, which brings us to this field of affordances, where there is loads of actions and each action, each task has some expected error Dynamics. We got to a task related context, which comes from selecting the task. And then we do some planning of sensorimotor sequences, we start acting on the world, and we get some error.

As we execute this task, then we have two types of monitoring, we have the typical momentous error that helps us go through the planning and correct the execution of the test. And we have a window of prediction error dynamics, which is compare to the expected error that this action had. And according to that, we are going to go to these emotions that tells us now the error is increasing, we have this loop here. So we go back to another task, before lack of core checking, then if something has changed, we still have physiological needs, or we don't, if the error is not so greatly increasing, it's more or less going fine, then we go back to this same planning to the same action. So it's a very nice model that we thought of, it's on the make. And we have many ideas from bringing this box diagram into the world and in our idealistic dream. What we're thinking on is something actually based on EMA. We haven't implemented this yet. But it's something based on this EMA. But now we have lots of other modules, we have some interoceptive internal model representation, exteroceptive model representation.

Anyway, so in this side, we have all the exteroceptive information, the interoceptive information, and we have some policies and a task and some error. This error is going to tell us how we are doing, how we can stay on the task. If the error is too big, then we can change tasks. So it's a bit of a mixture between the previous thing I told you and and this is how it could look in what happens top down. So when we have a task, this task is going to activate some policies and these policies are going down, to act on the world, we have again, some error coming up. And this error is somehow coded here. There is some monitoring so that we can go on in our policies. This is the momentanius error, if the error is very big, then we can go back here. So this is top down. And and this is actually bottom up. It's actually the error coming up all the way and coding here. And this is how we start the cycle with some tasks, policies, and everything else that is happening in the world. So we can stop there. I hope it's clear. We don't have direct questions from the audience. So I'm not seeing anyone.

Daniel Friedman: We have no direct questions, but we can definitely accumulate them for the roundtable. What is the relationship between prediction error minimization and free energy?

Bruno Lara: Well, It’s part of the process. I don't know what you mean. Within the whole thing of whatever you want free energy, everything that is happening, the difference between the expected states and what's actually happening in the world. So we always have inactive inference or in free energy, you always have an error, what is happening in the action in the world. So through this prediction error, is how you are we believe it's going to happen, like the learning is going to occur.

Daniel Friedman: Well, thank you very much. Hope to see you very soon. This next presentation is going to be by **Matt Brown**, **“Real Time Robotic Control through Embodied**

Homeostatic Feedback". So Matt, thank you very much for CO organizing, and for also joining to present. And please take it away.

<u>PRESENTATION TOPIC: "Real Time Robotic Control through Embodied Homeostatic Feedback"</u>

Matt Brown: Thank you for having me here. And that was a really great talk. I have some follow up questions for later. My name is Matt, I'll be talking a bit about a long running research project. And I hope you guys find this interesting. Here's a quick high level description of the project. It's an alternate way of looking at the generative modeling process built around homeostasis from the bottom up. This approach is very different, a bit of an unorthodox approach. And I'll be going into a bit of detail about how this works. You've probably read it, but the short version is based on theories of Ross Ashby and his homeostatic and it's a new adaptive model that uses via homeostatic feedback through an environment and itself. And I'll be showing some demos about applying this to robotic control that I've been working on lately. Quick agenda, I'll be talking a bit about the project background, where it came from, because it is unusual, I figured some background might be useful.

Then we'll be talking about how homeostatic build networks, self models, and what that means and how those function. And then I'll be talking about plugging those into environments and how embodiment works and how synchronization functions in this process. And then I'll be doing some demonstrations, showing this working with robotics. Just to give you background on myself, I'm computer scientists, mostly, I'm not much of an academic. I've had a few published papers, but not on this particular topic. I've been obsessed with the mechanisms of thought for most of my life. I've worked in the video game industry for about a dozen years, and then worked in deep reinforcement learning for a number of years. And also, back 20 years ago was worked in software radio at the spectrum, which became Genu Radio that'll be relevant later. Today, I'll be talking about work that's now ongoing at my startup softwares and talking a bit about the history, will help explain what I'm doing. This started about 2006 and 2007 with deep learning was new hot thing, I did a big deep dive into it, really excited about it. But I was in fact quite dissatisfied. And I felt that deep learning and this approach of using neural networks didn't really provide much insight to how learning works in natural systems. And even in the last few years, I feel we have this amazing hammer with deep learning and everything suddenly looks like nails. And we need to take a step back and look critically at what we're, what problem we're trying to solve.

So for me, I was looking for new approaches and the nature of agency and goals, goals in terms of what are they and how do they manifest in nature, semantic information versus raw information, how to process sensory signals become meaningful. And also, I wanted more insight into how time played into this learning process. And in particular, I was looking for medium agnostic approaches, not in yard specific, how do plants and single celled organisms deal with their world? So I started by reading a lot. Going back in time, there was a theory, I was a big fan of, I ran into Maturana and Varela And autopoiesis and I was really excited about that. But it was too abstract for me as an engineer, I think to tackle and so I kept going until I got to homeostasis and cybernetics, and particularly a cyberneticist named Ross asked me, and I basically became obsessed with Ross asked me, you know, to still am to a certain degree, and he's not a part of most computer science programs. So he's quite well known outside of computer science, but I felt is not part of my own education. And he's most known for things like the law of requisite variety, and the good regulator theorem. And those will be coming themes in the next three minutes or so.

So what I started doing is poring through Ashby's technical journals recreating his work, and in particular a device called the homeostat. So this is a quick slide to tell people about the homeostatic Ashby. We no doubt many people watching this probably are familiar with Ashby and perhaps the homeostatic, but it's worth going over briefly. Regardless, if you look up on Wikipedia, it'll say homeostasis is one of the first devices capable of adapting itself to the environment, and exhibited behaviors such as habituation with reinforcement and learning through its ability to maintain homeostasis in a changing environment. Ashby viewed, learning as adaptation and stability, and was described as an isomorphism generating machine. And most importantly, for me, I use his feedback to generate hemostasis via a property called Ultra stability. So I'll be talking about that here. There's this description here from one of his books about it. But it is quite tricky to reproduce, I had to go to his personal technical journals, and lots of iterations before I got it working. The key for me was Ultra stability, which is a very strange kind of property. But it is the individual node property, within this four node homeostatic that enabled this general group property of homeostasis to take place. Its core of the function of how the homeostatic works. And it's in the property and implemented by individual nodes, using a simple set of rules, that gives rise to group homeostasis. It's comprised of a double feedback loop, where like the low level feedback loop performs like a linear transformation. And then a high level feedback loop modifies this linear transformation. And this design to seek equilibrium meaning output of zero, if you can think of this, each of these knows the seeking equilibrium of a state of zero, every choice of a linear transformation is a prediction of a type. And so the result of this linear transformation every moment, accumulates prediction error as it seeks zero prediction error. So it's an interesting goal driven process that works through multiple group process.

Because it's a more in depth description. The homeostatic basically constructed of four individual ultra stable nodes. And the network as a whole creates an adaptive dynamical attractor set as a self-consistent reinforcing self-model. Ultimate stability powers its stable states, space exploration, through the law of requisite variety, and can be seen as a network of reciprocal constraints. I had this interesting letter from Alan Turing to ask me back, when they were members of the radio club. And as he was getting some notoriety, hearing, basically disagreed with Astris approach. And this letter here, he suggests that Ashby simply stimulate his homeostat in his Turing machine. And while true, Astris actually was a bit of taken aback by this, because it misses the point. At the time, the debate was all about analog versus digital computation. And, what was useful to the world was most critical.

But there was a bit of a conflation here, in terms of what Astrid was trying to create, which was something more along the lines of universal adaptation or universal cognition, maybe, versus Turing's universal computation. And this conflation issues still haunts us today with deep learning and whether or not they're intelligent. So having built, so essentially, I took Turing's advice and simulated, and particular 20 years ago as part of the spectrum ware project which is pioneered software radio, which is now part of called Geniu. And so stole methodologies from this approach, where I created the homeostatic as a digital simulation of a continuous analog system or device. And so that's the approach I took. I started by pulling through Ashby journals, and experimented with different implementations and approaches of his directed analog machine. Once this was functional, it was simple enough to abstract down to very simple minimal process.

Once it's functional, you can start taking pieces out and see what what breaks it and what doesn't. And eventually, this effectively simplified down to a dynamical attractor definition for ultra-stability that could be connected into arbitrary network topologies. And the network as a whole can be seen as a self model. Each node is trying to predict its neighbor as it seeks equilibrium, and the local Ultra stability tunes nodes, local connections, and the resulting positive and negative feedback loops that it is personally a part of. And Ultras really tunes these as a group of these overlapping feedback loops such that they reached a homeostatic equilibrium. And that means that the local prediction community prediction error drops to zero as well as the output from each node. And these overlapping loops become self reinforcing and self repairing. And it's this final self predicting set of loops that maintains a self model. At homeostatic equilibrium, this model converges and considered self consistent. It is composed of these homeostatic feedback loops that maintain the network at a critical state, meaning that the network is highly sensitive to prediction error and mean the smallest to smallest prediction error can trigger global structural changes amongst these feedback loops. And this process can also be seen as summarization, which I can talk about a bit later.

So let me show a quick demo. I'm going to skip to the original homeostat here. And I'm going to show a quick demonstration of what this actually looks like for a 20. Note homeostatic, it takes a bit longer. And it's a bit more going to demonstrate, let me switch briefly here. You're seeing 20 single dimensional graphs, this is the accumulated local prediction error at each node of the 20 node, homeostatic. You can also think of this as 120 dimensional dynamical tractor or 20, single dimensional dynamical tractors. You consider these as phase space graphs for each of the nodes. So what you're seeing here is I have a pause, I'm going to move it along slowly, this has slowed down on purpose. And what you'll see is they start off very chaotically. And what happened is a couple of nodes will start stabilizing, then more will start stabilizing. And then eventually, the entire network will converge to zero prediction error. Now, this is unconnected to an environment.

So it's just predicting itself. One thing I like to do here, and I don't know how many people also are going to find this interesting, I want to show a little in depth look at what this final convergence and collapse to zero looks like. So what I'm going to do is I'm going to change this to auto scaling the graphs, meaning that as it goes to zero, you'll see the graph ranges drop. And, what you should see is, usually there's a pattern forms amongst the output nodes, that is consistent with every drop, what we'll see is, it's hard to see what 20 nodes especially I've gone a little too far, we're already at E negative 20 here, but what you're seeing is you're seeing the 20 dimensional drop to zero. And there's like a cyclical pattern to this. And every time it goes to this pattern, it drops down and other orders of magnitude. And this will go all the way down to the floating point error of my computer, which is about negative 46, I believe. And then it basically fails to function at that point, because it can't tell the difference in floating point error, can no longer function. And the whole thing falls apart there. But that shows you a bit about the process. Let me go quickly back to the slides. So that showed you a slowed down version of the 20 dimensional homeostat. And I wanted to show the 20 dimensional because it happens a lot slower, it's a little easier to see what's going on with four nodes. It's almost instantaneous, and it's hard to see the progression. So that seems like a lot of work for a model that doesn't really do anything and isn't connected to environment.

So we have this model that can adapt its internal structure to reach homeostatic equilibrium through this a self synchronization process. How do we use this to drive behavior and this next took me a few years, even though it's conceptually simple, but don't worry, it'll get complex really quickly. The short version is sensors and motors define how the agent is embedded into an environment. And the network topology defines the adaptive capacity of the homeostatic agent’s model. Sensitive definitions provide a mechanism to influence the behavior of the system by providing priors in the form of preferred environmental states. These acts as two dynamic priors, externally defined dynamic set points for the homeostatic adaptation. The motor definitions provide critical affordances for modifying the environment that provides the basis for future sensory predictions.

The first states of the sensors become the first outcomes of motors and the models behavior is bias as desired. This is probably most people on the active inference symposium are probably familiar with this idea. This slide is put together for the benefit of people who are kind of familiar with traditional deep learning and neural network approaches, to contrast how these networks function differently, because it's a bit hard for people to get their head around. The first is probably the most obvious is there's no back propagation here, only Ultra stability, which is kind of a local rule. This leads to huge sample efficiency and the learning is very structured meaning, you don't have to diffuse learning across, 1000s or millions of parameters, you only have to model the part of the, you don't have to update the part of the model that is miss predicting, or as part of a miss prediction. The other thing to notice is that this is not a temporal, most neural networks and deep learning networks are disembodied a temporal processes. This is very much a temporal process, signals take time to move from one node to another, which makes it inherently the whole thing very temporal. The resulting temporal relationships are important, actually, spatial relationships of sensors and motors end up getting encoded into relative temporal relationships within sensory signals and also vice versa, signal timings of the propagating signals within the network can translate into different physical spatial relationships amongst the output motors, for example, or the input sensors. So there's a relationship between temporal location relative timing of signals and the spatial location of sensors and motors and the physical embodied agent, the different regions within this larger homeostatic network will then be sensitive to different sets of motors, sense of sensors, based on their physical, relative location. And, by contrast, deep reinforcement learning deep for example, is an attempt to adding temporality to an otherwise a temporal static, deep learning models. The other way to compare these two is deep learning models are generally trying to be general function, universal function. Approximator, where this is much more generative, inherently temporal, the learning is very, different. And just to expand a bit more on the topics from the previous slide, the network diagram here on the right is very over simplified network, and it's a mix of visually explain how to think about some of these networks.

There's no forward or backward, no front back top bottom, only relative location from other nodes and from sensors and motors perhaps more relevantly. And it is common for people to look at the learning process as a sequential flow processing like sensing, proceeding, planning than acting. And instead, you have to think that this is all happening at the same time, emerging together is one whole perceptual motor system, not a traditional sandwick model. Time simply advances and we simulate the analog systems as signals propagate across the network. And you don't get input from the sensors, calculate the network and get the motors, you send them input to the sensors, you get out from the motors based and those motor actions are basically based on the generative models prediction of what it should be doing already before having an even since the world, so, what's interesting here from the model point of view, in terms of how this homeostasis works is the network's homeostatic feedback loops, come to be dependent on the expected sensory signals in meaning that the sensory signals become entrained in the homeostatic self maintenance processes, which naturally makes it grounded in the embodied experience.

In homeostatic self maintenance process is composed of environmental signals themselves as part of its predictions and expectations. Expectations and predictions for the consequences of motor actions are embedded in a single sentence through the sensors from deeper in the network, like on the right here, and they're sent to the sensors where expectation meets reality and prediction errors cascade backwards and modify the internal structure of the model as polymers model update. These and then motor actions are accompanied by these parallel sensory prediction signals that flow from the deeper in the network. The actions taken any Robots are not based on the latest input, but based on predictions driven from deeper in the network, from the same places that the sensory expectations are sent from. This may be familiar to those who are familiar with predictive processing or perceptual control theory. And the idea here is that where the sensors and motors meet the network, the network itself is trying to make those local prediction errors zero, meaning it's trying to anticipate the actual sensory experience through inverse modeling.

So another just kind of quick look at how to look at this homeostatic processes through synchronization. This process can be seen as generating an adaptive synchronization manifold between an agent and environment, around minimization of prediction error. This is kind of looking at synchronization. That's prediction, when two senses are synchronized, they can be thought of as predicting each other anticipating the others notions, and individual nodes using ultra stability, or using ultra stability to learn how to predict their neighbors. And when equilibrium in these nodes are kind of synchronized through these feedback loops. And the synchronization spreads from individual nodes to whole network synchronization, and ultimately, out from the motors and back and through the sensors, in a synchronization manifold between the agent and environment.

To say it another way the the overlapping feedback loops interact and synchronize with each other as part of this homeostatic self maintenance. And as these feedback loops extend for motors through the environment, the sensors, the model gains the ability to anticipate the consequences of its own actions. And the capacity to synchronize internal states with something in the external world, that synchronization means that internal states will come to resemble, one that was come to resemble the internal states of the other. This is along the lines of, the good regulator theorem. When at this, synchronizes homeostatic, state, it's also in this critical state, I've mentioned this earlier, where it's stable, but it's sensitive to local prediction error. So the meaning that this critical state, may is maintained as long as local prediction error is maintained within a certain threshold. But otherwise, the smallest prediction can trigger global structural changes within these feedback loops, in order to better predict the future in order to maintain a synchronization network must be able to converge to equilibrium faster than the environment can destabilize it. And so there's network update rates, where we have to maintain, this fast movement, and this is in line with the law of requisite variety, where we have to make sure that we can explore state spaces faster than the environment where you're attempting to control. And as long as the homeostatic network can re establish the stable feedback loops faster, then then this synchronization manifold will be maintained. And synchronization is an interesting thing, especially in the context of robotic control. Because, once two elements are synchronized, let's say you have a sub network that's synchronized, and two nodes that are not directly connected, can end up coordinating without any communication between the two, because they've been previously synchronized, their behavior will end up being correlated as well. And in case, it's interesting to think about, what is the structure of these kinds of feedback loops and this generative model, and the way I like to think about it is, I've been in a color key meaning, a hierarchy is top down construction. A dynamic hierarchy is more a bottom up construction, where the parents are composed of the children, and dynamic in that, as the children change their own self definitions, the parents are likewise change.

So it's constantly shifting and changing over time as the children redefine themselves. And this structure is very useful as a general model, as well as a small number of individuals to kind of reshape the hierarchy very quickly, as part of an ongoing dynamic process. So I'll switch over and do some quick kind of demonstrations showing how this ends up. Why would you actually want to do this especially in the context of robotics? So the first thing I'm going to show is. This is the demo I put together a couple years ago, why would you do robotics like this? What is the point and what is robustness mean? And what does additivity mean, in the context of robotics. So hopefully you can see now my screen, this is a simple modification of an opening a gym called Richard and it's been modified to add a single texture joint here, and the reasons will be obvious here in a minute. But this is a simple tasks, the model has to get its end effector to the target position.

And this is using these homeostatic models here. But here's what's interesting I can do and this model hasn't seen this situation, I can disable the auto motor, for example. And it will basically, on the fly, figure out how to achieve the goal, just by updating its internal model and saying, this motor doesn't work anymore. Let me modify my model of the world, I can turn that back on, and he'll start using it immediately, or it will start using immediately, I can do the same with the internal motor, it can turn that off. So it figures out the inner motor, I have no longer have access to, let me update my model. And I can again, turn that back on, and it'll start using it again. So this was a simple demonstration I made a couple of years ago, to show why you would want to do robotics this way in that you can kind of get this real time adaptation to unexpected situations, due to the the generative model that's constructed this way. Now, let me scoot forward a little bit to more recent work. So this is something a little more recent, a little more complicated, we made the goal is a little bit more complex. And we've used a full six degree of freedom arm here, this is actually a fetch robot, mobile arm. But something a little more realistic than like a toy problem. And I'm continuing periodically here, retargeting the desired angle for this valve. And so this is a robot that turns valves. And what I've done is that I can periodically change the setpoint, where how it sees the world, basically, user defined goals by defining preferred states of the world. And then the homeostatic model basically figures out how to control the robot to effect the state of the world that it wants. I'm hoping here every 30 seconds, it will randomize the bow shape. The square one here is the simplest one, let me add some random motion and random orientation. The model has not seen this before, either. So it learns on the fly, how to deal with this kind of moving shape. As I do it, I can also do the sinusoidal motion here.

So imagine it's on a floating platform, where the rotation and the position that kind of moving through space, here we go, now we got something more interesting. So now we have still moving through space, it's a circular valve, here's something a little harder to turn. And what I'm going to do is I'm going to make it very slippery. So imagine that I've just poured oil over it. So now it's having to deal with a really slippery valve here that it has to turn into, still manages to do it, even though it's really hard. But you can get the idea here, is if you do the generative model in this kind of sample efficient way, you can get natural, adaptation to whatever it's experiencing in the moment here. So maybe I'll do the brand emotion again, maybe that's interesting. But you can throw at this, and he'll deal with it. Next steps are basically improving automation and tools. My startup is basically developing this for real world use, and adaptive situations where you need fine motor control, and dexterous object manipulation in uncertain environments. On the technical side, we're looking at, scaling up goal specifications, and topologies, which are related, as well as, deeper temporal horizons in both directions, planning ahead and recall. But that's all I had for today. And I look forward to the questions during the the roundtable in a little bit. If anybody has questions.

Daniel Friedman: It was great. Maybe one preliminary question, what settings do you see these implementations occurring in first and then the other question in order or if it's your preference is how do you see the homeostatic network related to the analytical first principles foundation And of active inference as we know it today.

Matt Brown: I didn't talk much about active inference, because I figured everybody else had done it pretty thoroughly. For your first question, use cases we're looking at are things that are just beyond the ability of current robotics. The idea here is the software could be put on any old robot and provide adaptive capabilities for some things. We're pretty open ended in terms of what we're looking at in terms of use cases. Right now, our current use cases are in like, energy, and manufacturing, and particularly, this is a fair amount of stuff that still has to be done by humans that could be pretty easily moved into robots, if they had, a little bit more capability. And then in terms of how does the homeostatic networks kind of fit into the active inference framework in general, and I kind of touched on it a little bit in terms of how these ultra stable nodes work in the framework of homeostasis, if you kind of think of homeostasis as the network trying to seek, global equilibrium, what this means from the ultra stable nodes point of view, it means that its local output state is zero, and that local output state is the result of an accumulation process of this linear transformation.

So here's this ultra stable node, what it's doing is, it's doing a search, it's doing a search through what are the right linear transformations that make my local state go to zero. And so in that context, you can kind of think of every time the ultra stable node updates its linear transformations. This is updating its local model of the world and making a new guess about how the world works. And whether or not that's useful for the purpose of global prediction, depends on whether or not it makes that local value goes to zero. So there's a lot of threads here in terms of expectations, and prediction error flowing through the network. But it's a much more distributed process, it's much less clear, like, what part of the model each node is taking place. Because each node in the network, when it's changing its linear transformation, what it's actually doing, it's slightly redefining of all the sub networks in the network, it's in all the loops that flow through that node, it's making a small change too, so each node in a certain way, then has effect on all the other networks that are connected through his feedback loops. And all those other nodes also have impact on its signals that are flowing through it. And this is reciprocal process that kind of builds this generative model. I'm not sure if that's particularly helpful.

Daniel Friedman: That's great. If I could make one more question, and then we'll bring Adam Safron on in a minute or two, the letter that you showed was quite interesting. And I got the sense of this, like, multi generational Titanic clash between what you described as infinite computation in the discrete setting, with Alan Turing tape, and then infinite adaptation in the continuous setting with a generalized cybernetics. And so that's a very fascinating framing, because what people say about computers and continuous time systems, we're going to have to discretize. And so the implementation is stepwise. And that's what allows us to actually implement it on hard drives and CPUs and so on with the Von Neumann architecture, but then also in the background, or like even the water that we swim in, is this continuous time, the real time unfolding of perception, cognition action outside the sandwich model, outside of the discrete time.

Adam Safron: I really like to pick up on that. I wish I was more qualified to speak on such topics. I'm a computer scientist, so I don't want to speak too far outside my field. But I think you hit the nail on the head of my gut instinct on it.

Daniel Friedman: Alright, we'll take a short break and then come right back with Adam Safron. All right. Welcome back, everyone. We are continuing on with **Adam Safron**, **"Generalized simultaneous localization and mapping (G-SLAM) as a unification framework for natural and artificial intelligences".** So Adam, thanks a lot for joining and please take it away.

PRESENTATION TOPIC: "Generalized simultaneous localization and mapping (G-SLAM) as a unification framework for natural and artificial intelligences"

Adam Safron: I'm Adam Safron. I am a research fellow at the Johns Hopkins University School of Medicine at their center for psychedelic and consciousness research. And today I will be discussing a grand unified theory. Another one, but before I do, as was previously mentioned, and as is probably of interest to people watching this, I recently co organized a special issue of frontiers in neuro robotics with NC Polito and Andy Clarke, most of the submissions are already in, for you to read, and that will be closing up soon. There's also another special issue that I am co organizing with other active influencers and for Estonians for Royal Society interface focus on the subject of symmetries in mind and life broadly construed, ranging from symmetry breaking and dynamical systems to a gauge theoretic formulation of the free energy principle. This is actively soliciting contributions.

And so please contact me if you have anything along those lines. So in this work, and throughout all of it, my journey, I've been trying to understand the bases of autonomy and biological and artificial systems. Do we have free will? How does that work? Could we build autonomous agents that work like we do and have our capacities? These are the kinds of questions that have motivated me. Towards this end, I have been working on some fairly ambitious projects such as 'a theory of consciousness' that tries to bring together various theories within the free energy principle and act of inference framework. And also models of freewill in terms of the micromechanics of agency. Across all of this work, I take what I've called a Marya neuro phenomenological approach or a Neil Seth calls a computational neuro phenomenology, which I think is a better name. And roughly the idea is you take the core aspects of experience seriously as fundamental things to explain. And then you cross reference this with a multi level functionals handling or a Marian handling, where you can simultaneously analyze a system on computational or functional levels with the system, what the different aspects are for their adaptive significance, with their the function they're serving is algorithmic level the abstract way, the specific programs and operations by which this is achieved, and the implementation level or the physical realization of these. And so the idea is, you take this multi stack on understanding of cognitive systems, and you cross reference this with phenomenology, taking experience seriously. And this is my general approach and active inference with its associated process theories basically checks boxes across all those levels. You have the free energy principle, you have active inference, and you have predictive coding. And these various claims of different degrees of specificity really helped to flesh out this mutually constraining multilevel account of cognition.

But, more recently, I have been collaborating with roboticists, in here to particularly excellent bio bots, Tim probalan and Ozen et.al. And along these journeys, we encountered each other and there's increasing interest in machine learning and artificial intelligence in things like artificial consciousness. You'll have people like Ben geo talking about system to cognition, and more recently, even lacuna has been starting to take these things on with his Jeptha architecture, talking about world models of different kinds and how they might serve the functions of artificial consciousness. But for my collaboration with Tim and Ozan, we've mostly been focused on the specific problem of navigation, specifically a problem known as simultaneous localization and mapping, roughly the idea here is that.

Where am I in space? And what kind of space is this? This is a fundamental question for any active inference system, any cybernetic system. But there's kind of a problem here and that you're trying to map out the space, and situate yourself in it in the same time simultaneously. So, but to map out the space, it helps to know where you are in the space, but to know where you are in the space, they'll help to have a good map of that space. And so there's various proposals for different ways of bootstrapping yourself to degrees of certainty of what kind of maps or models are adequate for situating you in the world, in a particular location. And this is going to be important, whether you're a robot navigating through the world, or an animal foraging for value, you got to know where you are, to know what to do. So more recently, in this collaboration, which I've really found to be amazing, because I'm in awe of roboticists, and what they can do, it's like that Fineman quote of ‘what I cannot build, I do not understand’, that's what they do all day long. They're, introspecting, how do I work? They're going into theory, and then they're actually building a system in this back and forth iterative process. And so the collaboration here was, I'm looking at what ways can biological systems and specifically focusing on the hippocampus system. What ways can these inform navigation problems. In this more recent paper that I'm going to be focusing on more today called “Generalized simultaneous localization and mapping or G-SLAM”, we're reversing the flow a bit. And the idea is more than cognitive neuroscience and forming robotics. It's looking more to robotics to inform cognitive neuroscience, basically leveraging the precision they have, with characterizing these problems in the way they're in touch with the ground truth of engineering and Physical moving systems in the world. Using this to inform cognitive neuroscience. And specifically, the claim is that this slam problem is fundamental.

And that it may have structured a surprisingly, maybe shockingly broad range of cognitive processes. And that this might be a source of fundamental principles for understanding how high level cognition was achieved, with high level putting some scare quotes, but it is the things that humans seem to be, or animals seem to be particularly capable of doing relative to artificial systems and humans, in some ways, even more so. And the properties we want to recapitulate in artificial intelligence and machine learning. So some precedent for this came from work with rat slam, the seminal work by Millford Wyeth and Praisser, so I'm in this, they look to the rat, and it's hippocampus. And look, it's wayfinding and navigation abilities, and try to basically, reverse engineerities, there's a really excellent YouTube video that I'll post, I've watched it countless times, which just summarizes this process of building up rat slam from, these initial foundations of the ambition of folding, and more and more details finding, and this isn't quite working, going back to the biology, going back to engineering, and then actually showing systems that do the same things as biological systems inspired by those systems. It's extremely compelling. It like, every time I watched a video, I feel like I get something new, I wonder is, are these the steps that nature took and evolving these systems? I felt like, what if I'd been doing with my life all this time? Like, why didn't I find roboticist sooner and started talking to them.

So I'm very grateful to be part of the symposium. And so with their work with latent slam, what they're doing is they're tackling the slam problem using active inference. I'm not going to go into all the details here. But some of this was discussed. There's parallels with some of the architectures that are discussed previously. And Tim touched on this. So you basically have an agent moving through the world that has a variety of views of what it's expecting to see and poses. And this experience map as a trajectory of the agent through space and time. And then here would be a generative model description in the middle of this, where you have these conjunctions of poses and views, which are unfolding this series of transitions. Adaptively sculpted via your policies. But where there's this upper level, which is basically organizing this as spatial temporal trajectories, situating you, in some map or graph of space, and this conjunction of posing view, one places I found must be compelling is that I've arrived at these, is basically the primary modalities I focused on, from looking at the Systems Neuroscience. But this happens to be the primary things that are focused on for helping a robot to move through the world and posing view. Basically, for neuroscience, I focus a lot on systems such as the precuneus, as potentially enabling something like a mind's eye. And the lateral parietal cortices, is something like a live body and that these were coupled very closely. And that would make some sense, your pose would inform, your view and vice versa. But there's another detail you need for this to be an autonomous system, adaptive agent, which is not, where's my body? And what am I seeing, but where am I in space? And where do I want to go relative to the world and the various things that I believe are in the world? How do I pursue my goals in the world and so enter the slam problem.

But what's built Layton Sam, this is a very impressive architecture. Some details are described below, all these things governed by a singular objective function, where the agent is able to not just make its way through the world, but also its powerful self supervised learning curriculum, as you're moving between views, and pose and landmarks, each one providing a source of predictions for the other, training of the other, helping you to get a grip on the world. In terms of slam on to the things that are broader notion of G-SLAM, generalized Slam with this, would be a way of thinking of high level cognition. I'm particularly interested in these two operations. One is called loop closure and the others graph relaxation/node application, s3. But the idea is to mention, when an agent finds itself, in a situation where it's posed and view, is highly similar to something to what was previously encountered. This affords a potentially unique opportunity, you now think you know where you are in space. And so this is a really good opportunity to update your experience map.

And so it's not a good opportunity in terms of you have high confidence, but it creates a closed system, so you closed a loop. And so you basically have these different equilibrium points in this graph, which can be thought of as a map also. But because they're all chained together. These are sometimes modeled, like energetic spring systems. And they're all mutually informing and constraining one another. And so when you find yourself with a loop closure event, where you're in this highly familiar state, you then take this as an opportunity to refine your map. And so you will do very fine, if you're within a certain margin error of a location, that you really got it, you'll then take the overall nap and breathe and relax. And you'll basically move around the various dependencies of different nodes and space, the different landmarks to adjust, then have each one inform the other, inform the other. However, if you're past some threshold for similarity, and it looks like you're close, but not quite that you're a little bit different. If you're surprised, then, you'll duplicate a node, and then you'll create a new landmark. And so you'll have a new graph. And so this is basically a kind of structure learning. And there's a lot of work in Bayesian cognitive science on and within Active inference, a lot of open work, like how do we effectively do structure learning for handling complex domains? And I'm suggesting, and I think Tim Ellis, hopefully would agree, especially because we're reading together, would be that this provides a principal basis for doing structured learning. Now, what's interesting here, though, this diagram that Tim made, is that as you're mapping out this warehouse here, if you set these thresholds for identifying a node differently, if your graph relaxation/ no duplication thresholds are set differently, you get very different models or maps, you might get very different structures, or if you will, schemas or scripts. That's not the frame in terms of the slam problem.

But the claim here is that basically, these hippocampus suppose that place fields provide a basis for structure representations, many of which have resemblance is the kinds of things that were hoped for, and like good old fashioned cognitive science, and in neuro symbolic AI. And apart of what's hope for some of the aspects of potentially uniquely human cognition, high level cognition, require some sort of representational scheme, but if you set these parameters, this is the mean by which you arrive at representations and if these parameters say differently could give you wildly different representations, these would have very different impacts on the minds you might have, potentially including even things like cognitive spectrums, if we would apply this to biological domain.

And so there's some notion that, for instance, you could even potentially think of these parameters for the hippocampal system, which are maybe evolutionarily, were originally laid down as parameters for a slam problem for an animal, find yourself in the world, but where the continue to operate in terms of the mechanisms of hippocampus and internal plasticity, that if they're parameterize differently in different people could give you very different minds. And the significance of this might be difficult to overstate, in terms of characterizing human differences, might be some of the most important variables you could look at, for saying how people differ in the way they relate to knowledge in the world. And not just some clinical consequences, basic science, quantum consequences, maybe even helping you explain some of uniquely human cognition, the kinds of things that helped to get symbolic reasoning and cumulative culture off the ground. There's other proposals, they're kind of similar to this, **mad dog navigation perspective**, or slam perspective. JF Cloutier Hawkins out of Numenta has a proposal he calls 1000. Brains theory, technically, it should be called something more like 100,000 brains theory, where the idea is that there's a common cortical algorithm carried out by every single cortical column of doing this object model, the navigation of the kindness described with the compliment Rhino system. I find aspects of this to be compelling, but also very mixed feelings. And I can talk about that later with anyone who's interested. There's another research proposal in this spirit by **Chris fields, and Michael Levin**, where they're basically characterizing morphogenesis as cells engaging in a kind of wayfinding and navigation process of where they ought to be in this synchronization manifold of the phenotype. And so they're all finding their place, as chromocell, like signaling from a common hymn sheet, knowing where they are.

But as they're synchronizing, they're moving around to find where they are, this unfolding geometric melody that eventually becomes the phenotype of the organism. But the idea is that this intelligence of wayfinding at the cellular level, many of these mechanisms may have been repurposed and recycled and deployed differently for overt navigation, and that this is a frame for intelligence more generally, I found this to be extremely compelling. Although what I'm doing with this work is, I'm focusing more on the hippocampus internal system as a source of specific adaptations with specific properties. And a major transition unit and evolution, potentially also have some connection to things like Ginsberg and Joe Blanca as major transition markers and unlimited associated with learning. They have a lot of emphasis on hippocampus system and its homologs.

There's very interesting work that I'm only beginning to look into in the insect with the central complex and the mushroom bodies and the way they handle navigation, cross referencing the mammalian version, and the insect version would be really invaluable. And that's a major to do that I'm hoping Danny will help me with. So some other precedents would be in terms of this idea of generalized navigation that this would be a powerful frame for understanding cognition, comes from some older work with **SE and McGuire**. They found interestingly, that hippocampus patients, not only are they impaired in episodic memory, but they have trouble with episodic imaginings of counterfactuals of novel situations. And so they talked about this construction system of the spring, this core system for memory and imagining, allowing for various forms of sophisticated modeling and creative cognition. And this seems to have been part of what basically gave Dennis the confidence to go and found DeepMind. And this is still a core aspect of what they're doing there. And the race is on, for reverse engineering the system and the race is heating up. And some really excellent work would come from Timothy Behrens group, I believe he's still at UCL. They're showing like for instance, there's an architecture called the **Tolman Eichenbaum machine**, which I strongly recommend checking out. That's active inference compliant as a realization of the function of hippocampus system, they don't focus as much on navigation, although it can be used for that. And that's part of it, I'll come back in a second for the differences here. In this work, one thing that I've noticed, so they're showing basically, people categorizing these stimuli, where you have these birds with different length necks, and there's a kind of Morpho space, in terms of characterizing the features and their various dimensions.

And basically, they're showing hippocampus grid like representations, being involved in helping to map out this feature space. And so this is one example that's very commonly cited of spatialized cognition, is something that might not seem clearly spatial. But then the idea of g7 would be once we spatialize that, then to what degree in our sense making, is it actually navigation through the space. And so this process of spatializing and navigating through the space simultaneously, I would call that a slam problem. And I think a lot of cognition can be fruitfully framed in this way. And I'm going to go a little further on. So here's the Tolman, I can buy a machine. So his work is unbelievable. Showing relations among people within our hierarchical tree structures of their relations. Doing things like transitive inference of one property relates to another and a set of dependencies, but basically, using the hippocampus systems properties to navigate and manipulate the spatialized representations. There's other work from Deep Mind.

There's this other talk I highly recommended by Stach, unfilled at all at the main conference, it's unbelievable talk, talking about the recent work from Deep Mind to reverse engineer the hippocampus cells and the grid cells of the internal system as allowing for a variety of properties. Very similar to barons working and they collaborate together. But one thing that's interesting about this talk is she makes a point that this isn't just for tasks that are like physical space, this isn't necessarily spatial. I might challenge that a bit. And say that, we should basically always have a prior of looking for the spatial properties of any task domain, and then wondering to what degree can we frame this as a slam problem? And there's maybe two reasons for doing this. Maybe three. One is that basically, putting things into a common framework helps you to draw analogies across seemingly heterogeneous domains. And this can be a source of insight, in terms of a common representational framework for assessing, sense making gives you an ability to have creative combinations from seemingly different domains. The other reason is, the hippocampus system, this was specifically probably what it was selected for. This is a mapping system for a animal forging through value, through various spaces. And this isn't just evolutionary, but this is also developmentally an ongoing, this is an ongoing problem, we have not transcended this, we are still in space, we still constantly have to move through space, and situate ourselves through spaces, physical spaces, and also conceptual spaces.

This is part of the reason I'm really emphasizing the slam framing, because hippocampus system will never lose this job description. And the idea is that understanding the ways in which is parameterised is specific opposition realizations, I don't think that's a word. It's essential to keep in mind this ecological significance. And so this is all within the spirit of, a broader view in cognitive science called ecological rationality, which is go back to the origins and try to understand, its Tinbergen is, quote, ‘nothing in biology makes sense, except of a light of evolution, take that very seriously and run with it’. One thing that G-SLAM’s perspective gets you is connections to foraging theory. And so, if you're thinking of an animal going through the world trying to extract value, resources are often patchy. And so as you're moving through the world, you might be balancing exploration and exploitation with a sector, if you find a patch might be good to exploit that forbid, if it's particularly juicy. But then as that patch dries up, maybe it's time to go explore. And then you want to adaptively move between phases of exploration, exploitation, staying longer in some places, and then moving to other places. And so these jumps, other places, when a patch starts to dry up, and these are sometimes known as lovey flights.

And this is playing actually into some of my work in psychedelics and that informed by some really intriguing suggestions from Matt shines group. The idea is that's one of the mechanisms impacted by psychedelics might be potentially facilitating these lovey flights, where you can think of more creative cognition as involving more exploration, more broad associations. And foraging theory, it's extremely rich and well developed. There's all different modes of foraging that could be thought of as different modes of cognition, there's specific hypotheses and connections to formalisms, like the marginal value theorem. So you would have like a hypothesis that, When do you leave? Well, in the Marshall value theorem, you leave a patch, when your current estimate of value drops below, what you think the average rate of return should be? So this then, gives you basically, like, you can now characterize people, where are they, relative to these different normative models. And this idea is, maybe hasn't even older, vintage or maybe newer relative evolution, but old relative to discourses, in terms of the art of memory, and the method of loci, memory, especially before we wrote everything down, or when writing things down was expensive. And even now, to have something in your mind, where, it can be at hand, where you can retrieve it to have a well curated set of knowledge, it's essential. And so one of the best tricks that were discovered, is you actively, intentionally spatialize your knowledge, you actually create a physical place that you visualize, and you move through it. And at each point in the space, you've placed different things you want to remember. And part of the reason this works so well, almost certainly the core of memory and hippocampus system, is actually involved in a process of easy spatial mapper, that's something I would argue there's connection to some other warthog of science back again into it now, but like multidimensional scaling, where you understand potentially complex Domains, by mapping them on to a simpler and potentially more cognitively navigable space. With respect to multidimensional scaling, one of the early things that got people excited for about it was, its potential use for analogical reasoning, or establishing similarities between domains, it's a very important thing to know.

How similar is something relative to something else? Should these things be placed in the same category? One way of doing this was saying, when you do multidimensional scaling, and you play something like feature space? What is the distance between different things? And the further apart the less similar they are? But there are other models of analogical reasoning, and there's another race on to try to figure out how we do analogical reasoning. So some of these proposals, they would go on beyond something like multi dimensional scaling, but they involve specific structure representations.

But then we have a question, well, what's the ontological status of such things? Do they actually exist in the minds, we do actually have representations? Or, maybe these things are more like their virtualized or an actively realized or implicitly, I suspect, many of the structures, described and good old fashioned type of signs might not be biologically plausible, but they might be surprisingly biological plausible, if you actually have a system capable of adaptively, constructing graphs, based on your ability to extract value from these graphs, and situate things relative to other things. And so it's possible that some of analytical reasoning and even causal reasoning could be unlocked by having a good means of creating structured representations. And one of the things that Campbell system seems to be able to do, is create these graphs with a different place cells of that Campbell can be thought of as nodes. And so if you duplicate a node, you are now basically doing structure learning. You are complexified, this representation. So this comes into my work in other ways, such as models of goal oriented behavior. I'm not going to get into too many details right now. But here would be the Campbell system, you see, based on work of people like reddish that, and also on like Sam Gershman has a successful representation of model. But basically, you'll see these campuses a predictive now, what's being predicted is where you'll see these sweeps of activity that will proceed in front of the animal before and then which will predict what choice will do, what arm of a maze and Mikoto. And so, the idea is that the hippocampus system is the top of the cortical hierarchy, and that any prediction errors that are not handled elsewhere, end up get temporarily stored in this volatile memory system, which is also encoding these trajectories ot these series of equilibrium points of state transitions.

And that basically, you have prediction errors that are not handled elsewhere, make their way there, get temporary stored and you can have what's sometimes called semantic pointer architecture, where basically, as you're moving, as you're stepping through these various equilibrium points, So you can then unpack this as estimates of system and world in terms of operative policies and actions and what you expect at different points along these different trajectories. And so here I'm focusing on moving through a physical space, in this case making T. But I would argue, this is also part of what we do when we navigate conceptual spaces that we are deciding what branches do we go down? To what degree? Where will we find what kinds of value and that this is a similar operation, using similar procedures from common neural processes? More recently, I've been trying to extend this to models of volition, including free will. So this is less, explicitly slammed framed, but still the hippocampus at the center of it. And so here, the present moment of experience, has a thickness to it. This is sometimes called the specious present, or the remember present. And that it seems to vary that the minimum thickness of a moment of sensemaking seems to be about a third of a second, and the upper bound seems to be about three seconds. And that this seems to correspond to an epic.

So you basically can see the hippocampus system, whenever you enter a room, it'll tile that domain with a certain degree of granularity will create these hexagonal tilings of that space. And then within there, that's where you'll have these different attractors, these different trajectories play out, orchestrating the rest of the brain in terms of its dynamics to pursue these various goals. And so the runway you have to work with in terms of the thickness of the different rollouts for sophisticated inference, would depend on partially the shelf life, of this set of attractors before you have to refresh them in some way or they're set down an entirely new set, or try to recreate the old one, or prevent the remapping. And this will be related to some of what was just described with aerodynamics, in terms of how good of a grip do I have. So let's say you're going to have a poor grip on what's happening, and your prediction error is going up, this is not a good situation for you, that might be a good opportunity to stop holding catch fire, retile space, it a new set of operative policies for sophisticated inference. And so here, what I'm trying to do is show that different levels of agonism of the serotonergic receptors involved with psychedelics, 5g to a receptors are influencing the stability of these sets of attractors and the vividness with which you are doing these imaginings and of rollouts of actions into the future. And here, it seems that what you could potentially do is describe some of a dose response curve for something like psychedelics, where as the dose increases, the extent of rollouts become greater, you've stabilized them.

And imagination become more vivid and influence your policy selection more, because you have more confidence in what you're seeing. And so sophisticated inference, your imaginings are contributing more to your ongoing overreaction selection, up to a point. But then, at a certain point, the idea is you keep dosing the animal or maybe the robot, enter is more of a creative dreamlike regime, where it starts to lose coherence. And you see the extent of these rollouts of policy selection decreasing, things are becoming more vivid, but less coherent. And sometimes and this itself can occasion error, and potentially regrouping in this model. So the idea is that this would be a cognitive spectrum potentially, in addition to explaining some of the neuro phenomenology of things like psychedelics, this could potentially explain some cognitive spectrums whether we're talking about maturation, or aging, or when you first wake up to going to sleep, these different parameterizations of your mechanisms for sophisticated inference, helping to basically provide a neuro phenomenological handling of human, of what it's like to be a person and all the variations of it. So that should be it for right now. And happy to talk about all this with anyone who's interested. Thank you.

Daniel Friedman: Awesome. Thank you, Adam. Any other notes you'd like to add?

Adam Safron: I think that's it for the moment.

Daniel Friedman: Great. Hope that you consider anything and join us for the roundtable shortly. So thanks. And we'll be right back with the final presentation by JF Cloutier. This will be the final presentation of this interval. This is **JF Cloutier "Towards a symbolic implementation of active inference for Lego robots".**

PRESENTATION TOPIC: "Towards a Symbolic Implementation of Active Inference for Lego Robots"

JF Cloutier: I will talk about how I program Lego robots as active infant stages. This word contrasts with most robotic implementations of active inference, which are based on probabilistic inference. So I hope this will spark some interesting discussions. Well, first of all, I'm a software developer. I'm not a neuroscientist. In my spare time, while I like to code models of cognition, because I'm keenly interested in all matters, cognition and consciousness. And I run them on robots, because the real world is hard. And I believe that writing code for robots is actually a very good way to test my understanding and coding itself helps make abstract concepts tangible to me. So what do I want to accomplish? Well, I want my robots to learn autonomously, while they conform to the principles of active inference. This is the current version of my robots. They're two earlier versions, and is one in early development. And here we'll see my robots the left Karl, the right Andy, driven by the interplay of generative models for hunger, danger, avoidance and wanderlust. Let's see them in action. They navigate to space. The sheet or paper on the floor represents food. And they are attracted by the scent of food simulated by an infrared beacon on pedestals.

Because making a beeline to the foods, Andy is having problems getting traction and bumping into the walls. Karl is cautiously approaching, but we'll get a little bit too close to the pedestal. And this will engage its danger avoidance, collision avoidance generative models, he backs out and Andy is observing all this and he is backs up also, Andy approaching food and this time we'll eat successfully and he has noticed that Karl was freaking out and in sympathy for itself. And so while Karl is eating. So that was the robots as they are right now, after three iterations of this project. What does it take to implement an active inference agent? Well, there are three approaches, one could take the numerical approach, which basically puts the mathematic of active inference into code and runs that on robots. Another approach is to take a symbolic approach, where we have code functions that operate mostly on symbols of predicates, etc. Here we can see, we have the symbols for hungry, very danger, curiosity, etc.

But that's not the only option. Take ecoly, ecoly isn't active inference agent and its implementation is biochemical. Well, i didn't take that route. I went this symbolic route. Well, mostly because it's the familiar one to me. And it provides me with a better scaffolding for my intuitions and exploration. Also find that it handles complexity quite well. When I started this project in 2017, my first thoughts were to implement a society of mind. I had come across this concept decades ago. It's a theory of mind put forward by Marvin Minsky, 50 years ago. And its core, it says that intelligent behavior emerges from a lot of simple actors that interact in simple ways. It so happens that I look at it as an architectural principle, as well. So how does one implement a society of mind? Well, to me, it's clear, we use the actor model. The actor model is a model of concurrent computation that was introduced by Karl Hewitt in 1973. According to this model of computation, we have independent actors, which are concurrent processes, each one managing its own state. And the only way , an actor can interact or influence another actor is by sending it messages, in one if an actor receives a message, it will interpret that message, possibly modify its internal state, and as a consequence of fire messages to other actors. So a building a society of mind, using the actor model is quite a natural fit. I also happen to program in the elixir language, and elixir is a message oriented multiprocess language, which is based on the actor model. So it's a perfect fit. So here we are, it's 2017. I own two, Lego Mindstorms EB three kits. They're wonderful robotics kits with a nice choice of sensors, that mini motors and a computer, the EB three brick that controls them all. And I want to build a society of mind in elixir on my EB three robots. I'm in luck, there's a Linux distribution called EB three dev that allows me to run elixir on ahead the EB three bricks, so I'm all set. So that allowed me to start this project.

And this project, as I said, as completed three iterations. And I'm starting a fourth one. And we'll look at each one, in turn, reviewing the goals, and also the issues on covered. First iteration 2017, version one, the simple Society of mind, as I call it. So I implement ad hoc model cognition, it's not something that I took from research, it's something I made up myself, it's homebrewed. And let's have a quick tour. So being a society of mind is populated with actors. And we have the detector actors and their responsibilities are to interface with the sensors and to pull them periodically to generate presets, which are events, that are like all other events that the actors will produce are sent to the central nervous system actor, which is a dispatcher, which will then dispatch these events to other actors that are interested in them. There's a memory actor, and all events, are sent to the memory as well to be stored for a certain amount of time and represent the past, if you want to the agent and the other actors are able to query this memory in order to make whatever decisions they need to make.

One of the key actors are the preceptor actors. And what they do is, they ingest events, percept events, originally from the detectors and analyze them, maybe in the context In the past and produce higher level percepts, for example, a preceptor might be digesting a distance a preset from a detector, look at it and say, given prior distances, I'm getting closer to an obstacle and then produce the high level preceptor might say, I am getting closer to a obstacle, and I am currently close to it. So produce a percept that says collision imminent, and so forth and so on. Another important part of actor is the motivator. And motivator is responsible for deciding what the robot needs, what the robot wants. And it expresses this need or this one, as a motive event that is against centered and central nervous system dispatched in this case, to the behavior actor, and the behavior actor then takes this motive and acts on it, by emitting intent events that are listened to by the actuator actors, who translate these intents into actual commands and move the robot. But one key point is that the motivators actually are compete with one another, so that the most important need of the robot is the one that's expressed. So for example, being getting to safety is more important than satisfying hunger. Let's look a little bit into one of the types of actors, the behavior actors, the behavior actor is actually quite complex, it does a lot of work. It's not a simple actor, it's implemented as a state machine. And with every state transition, triggered by a new percepts, intents are emitted. And so we can have a behavior actor, which job is to direct the robot to the food.

So it works. So let's see Andy version one, moving about and trying to get to the booth, which this case is the blue paper on the ground. So we strive to avoid collisions, not always succeed, here it finds out it's stuck. Backs out, was around, doing a better job at avoiding obstacles. And now makes a beeline to the food, having detected it, approaches cautiously and feeds. So this worked quite well. But there were issues with this version one. Not necessarily think they was visible in the video, but the robot was frequently overwhelmed by a constant flow of precepts or the preceptor, the detectors constantly feed the precepts into the society of mind. And after a while, they back up and the robot starts reacting to old events.

And one solution was to actually put the robot to sleep once in a while paralyze it, let the events wash through the system, and then wake it up with a clean slate. So that was a little bit awkward. And another issue was that while there's no learning going on, the robot doesn't get better with each one. And given the model, it wasn't clear to me where I could fit learning in there. So for a version two. So I need to find a way to make my robots learn. And they also need to better focus and be able to have attention, so they can avoid the overwhelmed with all these unneeded sensations, also need more computing power. So I replaced EB three brick by a Raspberry Pi three. About the same time I come across Andy Clark's book surfing uncertainty. And I find that the predictive brain makes quite a lot of sense to me. I think it does a really good story about running and attention. So I decided to implement a predictive Society of mind. This is my first crack at it. I won't go into the details, I do in a companion paper. Let's say that there are actors who are managing beliefs, validating them, making predictions and taking action, to make these predictions come true. There's also an attention actor, for turning detectors on and off as needed, and a focus actor for prioritizing belief validation. I do it to do, some learning the robot learns what action correlate well with success, but that's about it. And there's the model does not feel quite right to me at this point. And they are bottleneck actors. An example there's only one experience actor, there's only one attention actor, only one memory and only one focus. And in his sight of mind, that just doesn't feel right, it still works. And let's watch Andy, on its first run, its anti version two, hasn't learned anything yet. So same scenario. So Andy has detected the food, we'd like to move towards it, but doesn't know which actions validate believes best. It smells food, but still now it's heading into the wall. Or indeed, is being quite the unproductive Aaron's quest for food, it's a little bit painful to watch, but stop. Now he's Andy 3rd runs later. And it's much more competent about matching beliefs and actions. Now it's food and very competently makes a beeline to that food, now the approaching, obviously a very different Andy from the naive one. And here we go. So it worked. But still there were issues with version two.

First, the model doesn't quite feel right to me, it doesn't quite capture. Something didn't feel right about it. And they were model bottleneck actors as well, which is not a good sign. And learning was limited to action selection. So time for version three. I call this one a society of generative models. So I go back to the Andy Clark's book, and also read on the free energy principle. And it becomes clear to me that the generative models are actually quite central. In fact, it's generative models all the way down. So I get to work on a new model. In this new model, I have very few actors. There are Detector actors as before, to interface with the sensors, actuator actors to interface with motor or speakers, and whatnot. And the only other kind of actor are the generative model actors, the GM actors. And there's quite a few of them in this case here 16. And they do the heavy lifting, they do the belief updating, they are predicting, raising of prediction errors, the selecting selection of actions, and they are responsible for remembering their past states and actions. Each GM operates within its scope. There's one for locating food, one for avoiding obstacles, one for a detecting approach to obstacles, and so forth and so on. The GM actors F parent child relationships.

The parent, the GM sends predictions as events, about what it expects its children GMs, to believe, even wedding itself, beliefs. And these predictions float downward, and prediction errors float upward. If a child GM receives a prediction about what it's supposed to believe, or it's expected to believe, and it's not what it believes in, it sends back a prediction error up to its parents. Well, that means that the general models of perceptions are in fact the uncontested predictions it makes, plus the prediction errors it receives and the GM updates its beliefs, based on these perceptions. And given what it believes, it may decide to take some actions and then raise intent events that reach the actuators, know what it's like before, the generative models are grouped into different areas of concern, there's being which is responsible for deciding whether we're in danger, we're hungry or we are afraid, there is the danger GMs, which have to do with clearing obstacles, trying to stay in well, avoiding collisions with other robot and whatnot. Then are hunger GMs that have to do with eating, seeking food and etc. There's the freedom GM, which I call the Wonder last a GM, which basically says Well, I'm either in danger and or hungry. So let me roam around. And finally there are these two, ones here which have to do with a guessing the intent of the other robot. And we'll go into more details with these two. So let's look more closely at the GM actor. Remember that the GM, as parent GM and child the GMs that predictions flow downward and prediction errors flow upwards. Let's look inside. A GM defines one or more conjectures. A conjecture is a potential belief. For example, whether I know where food is, or whether I'm about to collide two different conjectural beliefs. A belief may either be a goal, that's a belief we want to make true, like I'm eating, or an opinion, which is a belief that I want to validate, for example, that I am approaching food. A conjecture is typically activated, when the GM receives a prediction about the conjectured belief.

And a conjecture knows how to check its associated belief to see if it's valid. It knows how to make predictions, given that belief, and how to decide what actions to take to either achieve or test the belief. A GM learns how well ultimate courses of actions policies correlate to achieving validating a belief. It also keeps track of which child GM trusts more, did they send competing prediction error, so it does precision weighing. And each GM actor works in its own time, it's a concurrent process. And it operates one round at a time, and we'll see what round means. And it remembers its fast routes, its best perceptions and the predictions it's received in the past, its past beliefs and actions. So now let's look at the lifecycle of a GM actor. Well, as I said, a GM actor operates round after round after round.

So what's around first, when round is started, GM carries over the perceptions and beliefs from the previous round, it doesn't start from scratch. And if it's in the midst of trying to achieve a goal belief, it may, starts at its new round, activate conjectures for that action belief. And, as a result, sent predictions to child GMs. Once we're done starting, the round is active, and then the GM actor just sits there for maybe, 300 milliseconds waiting for events. Events like predictions coming from above, from parents that will then activate conjectures, trying to prove that the predicted belief is actually true, this will cause predictions to be sent to child GMs. And as a consequence, maybe prediction errors will come up and the GM will update its perceptions. When the round is completed, either because we've heard from all the children or because time's up, the GM completes this current round, it updates precision weighing, keeps it stressed, it perceptions updates, its beliefs, as a result may send prediction errors because your beliefs can conflict with predictions that have received before, it updates its policies and decides on a course of action, since intense, and notifies throughout, is completed. And we continue to go round after round after round. I mentioned that there were two very interesting GMs in the society of generative models. These are these two GMs. They represent my little foray into theory of mind. These GMs are dedicated to guessing what the other robot is doing. So each robot observes the other and detects patterns of movements and infer intentions from these patterns. There's only two kinds of intents that are inferred. One is that the other robot has detected food and is making a move towards the food or that the other robot is in danger and he is panicking.

Now, how does a robot see the other robot? Well, in addition to the array of sensors that already had from previous version, I've added a new sensor at a 360 Beacon seeker and what this beacon seeker sees, is the beacon on the back of the other robots. So each robot has a beacon at it's back, that broadcasts a 360 radius circumference angle. It signifies here I am. And the other robot can detect how far the other robot is, at which relative orientation. So that's a one robot here, Karl is making a beeline to the food. Andy has been observing this, and seeing the pattern of movement, which is a very straight trajectory. In first that Karl has detected food in his home it and may decide to follow Karl and get to the food as well. Another pattern of movements would be a chaotic pattern of movement.

And Karl, I'd be backing away in panic from hitting the pedestal. And Andy was observing this and noticed that this kind of chaotic pattern and inferred that a Karl was in a panic and decided to get into panic as well, if you remember the video, the beginning of the presentation. So this is going well. But we all know debugging is hard, I find out also that debugging societies of mind on robots is very hard. In order to help myself, I developed a simulation environment, as simulated embodiment, which allows me to observe what goes on inside a given robot. It helps for debugging and it helps for experimentation. In the simulation world, my robots, virtual robots live in a grid world. There are obstacles the blue tiles, they are got a darker areas that the robot tries to avoid, which are represented in the black and gray squares. And then there's the food, which is the green tiles here. As the robots navigate that space, by using their society of generative models, I can see where each robot is in terms of its state. I can see where it's located, I can see its orientation, when it's last said, what the action is executed. And I can see the state of its virtual sensors and virtual actuators. I can also peek inside of the various generative models of a robot, that here I'm looking into the avoiding obstacle a GM of Andy. And I can look at the state in the current round or in past rounds. And I can see which predictions came in, which conjectures are activated. What are the current perceptions, what beliefs that the robot holds at the time, and what actions it thinks are going to more likely to work and what actions it is taking. Very, helpful. But this moves really fast. And so I can actually slow down simulation and even pause it and then look inside the various generative models and see if what's happening and what I expected would happen. So great body debugging tool and experimentation tool. So I'm quite happy with version three. It aligns quite well with the active inference ontology. There are no bottleneck actors. But learning is still limited to selecting action policies. However, I think that the version three sets the stage very well for the new iteration, and this one has an ambitious learning agenda, and it's just getting started.

So version four, starting now. I call it active inferencing. So here's what I want to achieve. As the robot interacts with its environment, and, learns how to maintain it, I want for it to learn how to maintain its homeostasis, by growing its own society of generative models. So instead of being given the apiary set of generative models, I want the robot to learn that set. Not only that, but I want each GM to learn its own capabilities, I want it to infer, its logic programs that when executed will infer predictions from perceptions, will infer beliefs, also from its perceptions, and infer policies that will validate or invalidate its belief. So how does one do that? Well, there's a very interesting paper that bound which is called **Making Sense of sensory input** written by Richard Evans, and all from a deep mind and it answers the question of how do you learn a causal theory that explains a sequence of sensations. And once you've built that causal theory, you can then apply it to predict what the next round of sensations or perceptions will be, and thus make predictions about them. Just to read from the beginning of the paper, making sense involves constructing a symbolic causal theory that both explains the sensory sequence and also satisfies a set of unity conditions.

Now, Unity conditions are actually a set of constraints derived from Kant's philosophy that ensure that all the pieces of the theory have form a coherent whole. Semantically speaking, I won't go into the details, but it's quite fascinating. And the paper goes on, making sense of sensory input is a type of program synthesis, but it is unsupervised program synthesis. So the paper presents an app perception engine. This is the software that will generate infer causal theories from sensory data. It's a code generator, what it does is, it synthesizes logic programs that implement these causal theories. And when you run these logic programs, you can predict incoming sensations. So essentially, a perception engine generates predictors. And the way it does that, is it searches or predictor logic programs in a space of potential possible logic programs, it's a search problem. And the search space is extremely large, of course, so we need a way to constrain it. We need to apply strong inductive biases to restrict the search. That's where the unity conditions come in. So in order to derive its own predictor, a GM will search for good predictors using a perception. So give it a round, a prior round of perceptions. Remember that the GM has a memory of each round, and each round is set up simultaneous perceptions. Given that sequence. A GM will search a space of candid predictors for a good one. What makes a predictor? Well, two things, first, there's a scope. And then there's rules. The scope is essentially the objects, the rules will be about and the belief predicates that will be used in the rules.Well, there's three kind of rules, there's the static rules, which apply on a set of simultaneous perceptions at time n, and the rules validate and possibly also infer implied perceptions, missing perceptions.

An example of a static rule might be if the robot is that distance zero from an obstacle, it is also touching the obstacle, then there are causal rules and the causal rules, essentially, infer the perceptions at time n plus one, given the perceptions at time n. They predicted the next perceptions. An example of a causal rule would be if the robot is that distance x from an obstacle, and the robot is approaching the obstacle. In the next round of perception, the distance of the robot to the obstacle should be smaller. And finally, there are conceptual rules, which are rules that make the whole predictor hang together semantically, there are rules of mutual exclusion, for example, that can only be one distance between a robot and an obstacle, and rules of uniqueness. Rule of uniqueness that can only be one distance, for example, between two objects and mutual exclusion might be a robot cannot both approach an obstacle and be touching it at the same time. So the apperception engine will kick in for a GM, when the current predictor of the GM is no longer good enough for the jobs, like we've produced a predictor and now we have more rounds of perception. Isn't the predictor is doing a really bad job at predicting the next perceptions.

And then the perception engine will kick in and try to produce a better predictor for that GM. So that happens for all the GMs. And once we have a good predictor, the GM, given the current set of perceptions, in infer the next set of perceptions, does make predictions. So we talked about how a GM learns. But how about learning the entire society of GMs? How does a robot form its society of GMs through interactions with the world? Well, this was going to be guided by a a metacognition GM, that's something that's given. When the robot starts life. It has a basic set of detectors, set of actuators that is a given. And it also has a metacognition GM, it's also given, the metacognition GM, its role is to watch over and guide the evolution of a society of GMs. That's the acronym, for it to function though, each GM must act as a cognitive sensor, it must produce sensations such as our prediction errors trending up or down, do policies, particularly predictably impact my beliefs, or, very importantly, within my purview, is the robot's homeostasis at risks, these are convinced sensations that a GM will produce, will be absorbed, listened to by the metacognition GM, and that will allow it to update its own beliefs about all well the Society of GMC is doing, does it have sufficient coverage? Is each GM capable enough? And based on that may take corrective actions by creating new GMs.

And possibly, if one GM is not doing very well, that is stuck in around, removing it and replacing it with another. So that's the role of the metacognition and GM. So how can the robot tell whether it's doing better or worse than before, given what it has learned? Well, feelings, that's all. So a robot will have internal sensors for feelings and thinking about feelings of hunger, which increases with physical and mental exertion, and is reduced with eating, there's the feeling of pain which would go up with the number of collisions, but will be reduced automatically with the passage of time, simulating healing. And then I'm thinking also of the feeling of only which goes up if a GM is not learning anything, if it's logic programs are unchanged for a long period of time and but only goes away when the GM is learning. Feelings of have we balance, positive negative, I'm hungry, very hungry, negative balance, I'm not hungry at all positive balance and a negative balance signals risks to homeostasis.

And when beliefs are derived from feelings, with a negative balance or a positive balance, then these beliefs take on this balance and this is going to be used to prioritize actions because actions that promote beliefs with a strong balance, will be prioritized for actions that do not, so in other words a GM with very strong feelings will have its actions prioritize over GMs, that currently are wanting to take action but with from a less powerful feelings and if these actions conflict, then the actions of the GM with stronger feelings will predominate, will take over. Well given all this, what do, I think makes a robot an active inference robot? Well, there's many things but I'd like to think that its simplest expression, for me at least, and active robot is one that learns what to do in order to feel good, more often than not. So I'm hoping that this work will raise some big questions and give me some insights into them. For example, what is the appropriate knowledge that an agent must possess to learn autonomously? What makes unsupervised learning converge on competency diverge? And maybe a little bit more far out? What can growing a society of GMs learn from developmental biology? I suspect that there are principles at work here that they both share. So that's it. Thank you very much. Thank you to the active inference Institute for their help and encouragement. And the version three of my work is available on GitHub. It's open source, I can be reached on discord in by email, and the companion paper to this talk is available on sentimiento.

Daniel Friedman: All right, great talk, JF. We'll take a quick break and we'll be right back with the roundtable. All right, we are back. This is the beginning of the second round table. That's our last session in the second interval of the second applied active inference symposium. And some more may be joining. But I'm joined here by Adam Safron, Karl Friston and Jakub Smekal. Welcome too JF will be joining shortly. So perhaps to begin, if anybody would like to provide a reflection on a talk that was not their own? What was something that you felt like was brought to the table? What was a key problem area that was addressed? And how do you see active inference being implemented and adding meaning in that situation?

Jakub Smekal: I can maybe quickly, comment on JF Cloutier's presentation since was the most recent, definitely this symbolic approach to active inference is one that is perhaps not been that pushed forward in and like obviously, there are different approaches all around the field, but I feel that this particular perspective on pursuing the emergent generative models, which only have the very basic set up. But then the complexity emerges through the usage of elixir and prolog, was really interesting. And we talked about JF project, in the organizational meeting. It's quite a lot. But every time I think about it, it's really cool to see this implementation.

Daniel Friedman: Thanks, Adam.

Adam Safron: In terms of the recent one, the apperception engine, the content inspiration, and I found that to be really exciting, especially then taking some inspiration from Karl, some of the work and wondering whether basically, these categories, they not preconditions for judgment, but any sense making whatsoever, any sort of world with composition that can be navigated and parsed. And so, to see that work was being done with that level of sophistication was amazing.

Daniel Friedman: It is a thread that came up multiple times, with juxtaposing discrete time, continuous time and all of these. And then it's almost like another dialectic with the numerical and this the distributional approach to variational inference sampling, message passing, a whole taxonomy of approaches that we've seen for active inference models, and also models of perception, cognition and control outside of active inference. And so maybe, JF, if you want to to provide a thought on where you see the symbolic perspective coming from, and intertwining with active inference directions, and robotics, like we were talking about today.

JF Cloutier: Well, I think it comes in from different perspective, ones is explained ability of choices and behaviors. If the, robot is driven by symbolic reasoning, then it becomes relatively straightforward for it, to provide an explanation of its behavior, in terms of the chain of reasoning that led to it. So that's interest in and of itself, the other aspect is, when it comes to the perception engine, it has a an ability to develop a symbolic causal theory, from relatively small data set. So unlike a machine learning solutions, which require intensive learning process, which leads to an obscure causal theory you want, with the opposite trend engine, you have a relatively small amount of data that as input and a causal theory that's symbolically expressed as output, which can serve as a basis for explanation and justification and rationale. That being said, if as part of the process of perception, GM, deuces latent objects and deuces predicates. The meaning of these predicates are only to be inferred in context, because they're going to be called P one and P two and object O1 objective O2, you may by examine emanation maybe infer, that we're looking at a pretty good, that has to do with navigation and, avoidance, but that will not be clear. So that regard there are gains, but they're not absolutely clear in terms of explain explainability. But when it comes to active inference, that what matters to me is that the robots behave according to the principle of active inference and not necessarily by implementing the mathematics of it. So I don't think it's a contradiction. As far as I'm concerned, these are four things that are mind symbolic programming. That's why I'm doing it that way.

Daniel Friedman: Thank you. It's almost like in the textbook of active inference where we have the high and the low road. And here's the symbolic AirDrop, actually arriving at a similar place, although being quite disjoint, in its origins from the particular partition, flows on continuous numerical variables, a lot of the ways that we've seen things develop in the past several years. So welcome, Karl, if you would like to say hello, or provide any remarks on anything that you've seen at the symposium or any overview, thoughts on active inference and robotics?

Karl Friston: Well, I greatly enjoyed all the presentations, there's so many different perspectives. So I would margin my comments, will follow on from what people want to talk about. So I'm going to pick up on that last thing. So John Francois, symbolic dropping on from high. it was a really intriguing perspective. And it's a perspective that I've been actually forced into, in certain applications of the code old fashioned the mathematics of active inference. So it'd be useful to share that, in the sense of, when you write down discrete state space models, and use the maths of minimizing variational expected free energy to invert those models, very often, you're confronted with specifying those models with Boolean logic. If, This, Then, That. And literally in the code which you write to specify a particular tensor that map's from some causes to some consequences, you are literally using if and then statements and, and and, or statements in order to generate the tensors. Or, the matrices that encode probabilistic mappings, which now become deterministic mappings, simply because you're populating these tensors with zeros, and ones. So I didn't see an enormous opportunity here, to actually bring together the mathematics on the simple probability theory, this using, categorical distributions, or originally distributions of a particular, that where you're only dealing with zeros and one probabilities. And the logic apperception that you were talking about. I thought that was absolutely fascinating.

And one, thing that intrigues me is, if you can do that, then that there is a way of doing your searches of all the potential programs, or logical statements that are internally consistent with the evidence at hand. For example, I could build a generative model where I can be in two places at the same time, or two things can be in the same place at any one time. That's from the point of the genitive model that I write down without an exclusion principle. But when I now come to sit down, ask the question, is that model relative to another model that can be written down in terms of Boolean logic that precludes two things being in the same place any one time? Does that simpler model now provide a more a better explanation for the evidence at hand? So technically, what that means is I can apply the rules of Bayesian model selection to this model versus that model, where the model is a statement of propositions, logical propositions, and there are ways of automating that very efficiently called Bayesian model reduction.

And I'm wondering whether you could take a lot of pressure off the search for the internally consistent logical structures that you're dealing with. If you can cast it in terms of Bayesian model reduction, which quite simply is measuring the evidence, the probability of this sequence of outcomes that can itself be categorical, in this state or that state. The probability of that particular sequence of discrete outcomes, given this structure, this generative model that is articulated as a logic, and if you can do that, is going to be very powerful, because that speaks to a common theme, which most of us and you were talking about, which is this issue of structured learning. And what you're talking about a principled way to get the right parsimonious structures that have this, coherence, I can remember you are even taking him right back to sort of 19th century philosophy or 18th century philosophy, in terms of the constraints, will be really great to see whether that logical structure that philosophers like, actually could be discovered or disclosed using good old fashioned Bayesian model selection, there seems to be a close symbology there, with some of the work of people like Josh Tenenbaum, where he certainly article instructional learning from the point of view of radical constructivism using program searches and casting Geraghty models as programs and then trying to score the quality of these programs using a form of Bayesian model selection. And he claims to be able to do sort of millions, very effectively within a few seconds. Have you have you looked at Josh Tenenbaums work at all?

JF Cloutier: Not yet. But certainly will. Well, I wanted to make clear that the appreciation engine was developed by Richard Evans, in the paper, making sense of sensory input. And yes, one of the core issues is inductive bias. How do you restrict the search space, so that you can have a chance of finding within a reasonable amount of time, a logic program that is a competent predictor, and that's where Kant, synthetic unity of apperception plays in, as it provides constraints on the class of logic programs, which are acceptable, which are considered valid. And if I make a contribution, because this is work in progress, I would like to add additional constraints from the fact that we're not trying to generate one generative model in itself, but as is in the context of a society of generative models. So a general model will borrow its perception domain from the belief domain of other generative models, thus creating additional constraints. And as it searches, it will try not to modify the scope in such a way that it orphans, other generative models, so as the Society of generals model grows, so that was the same set of constraints that apply on reducing the search for predictor in any of the generative models themselves. So I'm hoping that as the Society of general models grows, so does the set of constraints that apply on the searches for any one of them. But the name of the game is very much in this, the richness and the strength of the inductive biases that are applied on search.

Daniel Friedman: Just to highlight a few pieces of what were addressed, then to Bruno or Adam or anyone who'd like to add, impressed on me robotics is radical constructivism, not in the sense of the constructing models, but also in the way that Adam described in terms of the relationship to the embodied artifact. So that is one interesting piece. And another in this quest to find the rainbow that connects first principles and analytic formulations, through miso scale, for example, computational code, all the way to the last mile in the cases, that we heard from Wen Hua Chen, in the previous session. Karl, when you described the way that Boolean logic enters at the level of execution was very interesting, and suggests that there is a brackish area, similar to that between discrete and continuous time models, in hierarchical modeling, but here, where the numerical and the statistical approaches to active inference are becoming connected to actual logical implementations and design choices that have to do with, which functions are executed first, are the conditions that certain things occur in. And so there actually is a meeting ground or an interface, in a way implicitly already. And so it is very interesting to see, How JF Cloutier's work on the generative model generation process is now approaching that intersection from the other side. And suggesting if you see a car coming from the other direction, there's a road. And now this high and low road network starts to grow more pathways. So Bruno, or Adam would be happy to hear any thoughts you have.

Bruno Lara: That's much our case, as I was telling you, we come from this other side of the story. And at the end, we have to make some choices on the implementations. And so far, we've been very focused on this self organizing maps, most of our work is on that. And that's actually one of the questions I had for all of you, what's your take on all these approaches, that we're trying to work coming from a different field, from a different point of view. And in a way, we are almost intentionally avoiding probabilistic approaches to active inference? So I don't know what's your opinion on that? That was the first one. And the second one is, a question for Karl, what do you see in the near future on all these things, so that we're working on prediction error, dynamics, and this monitoring of the error over time?

Karl Friston: I'd love to speak to that if I can. And, interestingly, it does actually also speak to your question, Daniel, I wanted to point out also that this notion of moving between continuous state space models and discretized state space models, is something that people in quantum computing and physics are going to keep their close eye on, because you get it all digital, than the opportunity for quantum computing suddenly raise its head. So there's also a very pragmatic reason to look at that transition. And als to bring in Adams point, not only was he suggesting that we quantize, discretize, spatialize, in terms of little tiles and places, receptive fields for being here, as opposed to being over there.

But he was also suggesting we do that in time. So the quantization of space time in a generative model, is a really important thing. Because, we could argue that's a step closer to good old fashioned symbolic AI that has a meaning in the folk psychology sense. So to come to Bruno’s question. So the big divide from my point of view, and these two generative models, that are of continuous states and time, versus generative models that are discrete states, and space and time, and clearly you need both, in the sense the world, that are roboticists, indeed me and my children live in is a continuous world. And I have to move around it, I have to control continuous temperatures and all sorts of things. And yet, it seems as if the intelligence is at a symbolic level. So what we're talking about is a hybrid generative model. And then the question is, how do you get the discrete parts to talk to the continuous parts? But if we just focus on the continuous parts? And to answer the previous question directly, as well, what I'm saying is you can't ignore the continuous bits. So everything you were talking about in service of self organizing Maps has to be there, at some level, it's a question of whether you can put a more symbolic logical structure on top of it, to call screen and sufficiently to resolve all the complexity. I love your work, I could see all the important issues in terms of representing uncertainty as, if you, the standing for the valence of how I am doing, so I was amused to hear that you're actively involved in probability theory. For me, everything you said was all about probability. It's all about uncertainty.

And that was true in so many levels. So just to answer Daniel's question to you, the relationship between free ended variational free energy and the prediction error is really trivial and very simple. It's under continuous state space models with Gaussian random fluctuations. The free energy gradients are the prediction errors, the sign of prediction errors. So it's really simple quadratic forms for the low probabilities. So self organizing maps that organize themselves in terms of responding to prediction errors, our systems that are performing a gradient flow on a variational Free Energy. Under the assumption you're dealing with continuous states, that have Gaussian by random Gaussian random fluctuations. So that's all exactly what would please me, if I was a probabilistic, committed to the probabilistic part of it. You're bringing to the table, though, is this dynamics of the uncertainty or the amplitude, the prediction error, the unsigned prediction error, the behavioral prediction errors over the separation of timescales.

That's a really important, move. I see slight homologues of that not formally identical, but certainly homologues of that. From the point of view of an engineer, this would be like getting the Kalman gain, right. If you interpret a Kalman gain on a Kalman filter, as assigning the right precision or confidence to the prediction errors, as they come in relative to the state estimators and your prior beliefs that you've accumulated, getting that right, having an adaptive Kalman filter, where you're actually optimizing the Kalman gain. That would be if you like the state of the art hierarchical Kalman BUC filtering, so if I was a psychiatrist, I would say this is exactly what goes wrong in people with schizophrenia and autism, is that they've got their estimators of the overall uncertainty or prediction error wrong. This is an explanation for false belief updating or false state estimation from the Kalman Filtering point of view. The other point that struck me in the early part of your talk was, as a neurobiologist, or motor control theorist, something that they would find very entertaining, which was the link between the ability to ignore stuff and sensory attenuation. I don't know if you've come across that in robotics. Certainly, in terms of motor control of the kind, you're using, which I would ascribe to the equilibrium point hypothesis like approach. So you're, putting your setpoint into the actuator, and you're letting the reflexes do the rest. But you've got to control carefully, how those prediction errors are used to drive the actuator and make sure they don't come back up and change your state estimation. So from the point of view of sensory attenuation, that is attenuating the precision, or the inverse variance or estimation of the overall amplitude. So finally looking at the long term trends in the estimated precision, is a really important way to see whether you've got the right generative model for this context. I noticed you're citing the work and that was really great insight many years ago, interesting from economics. He was working with economists at that time. So that's very important as well. It's all about estimating uncertainty.

Bruno Lara: Thanks a lot. As you can see there's, well, obviously, we come from this side of woolpert. And you can see all that literature behind our work we're getting there. And that's where we're going. That's what we're intending. And you'll see some work that we're going to come out very soon, that tries to bring deeper and more useful, making better use of these monitoring. And the other thing I was thinking is something you mentioned is this weighting of the attenuation. And that's always been in our mind, again, because of why can you tickle yourself and all these famous works? We have lots of doubts. We have lots of discussion with people about this attenuation and the precision weighting. And that's what we are now trying to implement, again, using self organizing maps. But we tried to get results quite soon. And thanks a lot.

Karl Friston: That's really important because soon as you can get dynamic attenuation, or gating, in play very much in the spirit of what was implicit in Matt's homeostatic architecture, genuinely, you can talk about your robots attending to this or ignoring that in the right way. And you're starting, quite close to now, sentience, because he got attention in the mix. You've got some metacognition, in your self organizing maps, which is something which is much closer now to sentient intelligence, as opposed to a reflexive control.

Bruno Lara: That's the idea. Let's hope for the best.

Daniel Friedman: So a few points are then Adam or Jakub or anyone. Active inference is inference about action. And it also uses action as one of the ways to reduce uncertainty. And so it's a very tantalizing parallel with quantum active inference as being about quantum systems, and potentially using quantum in some way to run these models. Another point was in the recent folk psychology paper, with Ryan Smith et.al, there was a distinction of how increasingly cognitive and symbolic functions, were being played by decision making active inference in the discrete setting, while more motor behaviors can be played out by motor active inference in the continuous time setting. And through this conversation, I'm seeing how, whether that is explicit or implicit, that decision AI to motor AI handoff, is mediated by a symbolic layer, either implicitly through the code construction, or potentially even explicitly with the approaches that we're exploring. And then one last area of some parallels that I'll like to hear from Adam or anyone else, self-organizing maps, brought up by Bruno have a lot of similarities with some of the graph operations that Tim Verbelen and Ozen et.al and Adams work was describing. And then the harmonic modes that Adam has described his work as well reminded me of the ultra stability that Matt Brown described, and some of these more classical models of Synergetics and multiscale, harmonic organization. And so Adam or anyone else, would be happy to hear any of those thoughts.

Bruno Lara: Quickly to answer, Adam. Adam is asking to what extent can self organizing maps be used as a model of experience dependent plasticity as implementing a implicit neural architecture search? I don't know exactly what you mean, with neural architecture search. But there is this literature on growing self organizing maps. So the usual, original architecture is fixed. But there is some implementations where you actually can add nodes. And they become more, they have more plasticity. And there is also the ones that don't stop learning. So it's continuously moving. So that helps you to not have a fixed structure and a fixed mapping of the sensory input. But it's moves us, there is new data coming, new input coming in. So that's the dynamical some and growing sums, if you're interested on that.

Adam Safron: Extremely well, I guess the intuition or question was that. So I'm sure there are plenty of inductive biases that will come equipped to help us converge on an efficient regimes of inference and learning. But I'm also wondering the extent something like a field programmable gate array, but that self organizing map, dynamics could allow for the creation of different regimes of active inference, to what extent as you're building up a hierarchy, a different level of it, based on where you are in this overall hierarchy or heterarchy, you might take on very different computational properties via experience dependent plasticity. So you learn the inductive biases, you need as grow. But come back around with self organizing maps, the locality and the topography of them. One thing I'm really curious about is the extent to which they can actually be used for modeling, enter vinyl and hippocampus representations, to what degree the different operations that are used for constructing these maps, would also converge with them the structural inference and structure learning that have been described for the hippocampus system. So I don't know the answers to that. But it seems like a potentially fruitful intersection that Daniel suggested.

Bruno Lara: So in principle, they are inspired from the ripple Campbell, activity and all the maps. And there's lots of proposals out there of different ways of moving them. But they would be very useful for what you want.

Adam Safron: As well, I'm talking about, a general question for me that I've been wondering about, is you're getting these structure representations potentially being afforded by these place fields at the Ripple Campbell system. But one thing I'm wondering is that these would provide equilibrium points, like Karl often will talk about the importance of structuring action and perception, by these discrete acts that seem to be unfolding in roughly Theta Frequencies. And this seems to be the timescale of coherent action selection for an organism of about our size that can do about the things we can do with the brain about this big all, brought in the same temporal register. But we might be stepping along these representations, in some ways, moving between these bumper tractors as somehow structuring cognition, by some representation. I'm excited by that. But I still don't have a sense like, for how far you go with that or ought to go. For instance, this is actually something that Karl said in the past, which is like before think of the architectural principle, think of the inactive situatedness of the system.

And so something I wonder is maybe you're getting this inductive bias of the hippocampus, neuronal systems, this high level controller, but to what extent are we implicitly doing things like symbolic reasoning, but the modes of enactment? To what degree could you do something like purely in causation, you want to do something as a dual operator, you could have some graph, some flow of inference, maybe even within that, Campbell system, or the hippocampus system and actually know for KA, brought up recently was bumper tractors in the colliculus. So maybe even atoms, like patterns or ocular motor motion is potentially providing, another means of accessing such representations and being governed by them. But to what extent is it to neuro centric, it's actually being realized more implicitly, by the overall contextualized functioning.

Daniel Friedman: Sure, to Karl, and then Jakub or anyone else who wants to talk?

Karl Friston: I wonder whether that is the interface that Daniel was referring to. How do you get from a necessary continuous Bayesian filter coupling with the world? Even with Karl and Andy, these things are moving continuous stays. So at some point, even if it's actually physicalized, there is a continuous generative model, self organization in play. And I'm reading Adams question, as is this to neuro centric to worry about bumper tractors, and the role of lateral inhibition, for example, in carving up receptive fields that could be actually written down as of basically a quantitized representation. For example, receptive fields in the 5 or motion sensitive areas can either be expressed as a sort of continuous preference for motion as a continuous function of visual velocity. Or you can say, No, this population is just encoding the probability that this particular edge is moving at eight degrees per second. So, you were asking, are we being tuned, Eurocentric in over interpreting the neuronal dynamics that basically to do the carving up into a series of either tilings and receptive fields or place fields, or in the context of stable fixed points, thinking about histoclinic, channels as your one way of articulating a discrete set of orderly organized, fixed points and how they are? That's the way that we should understand it. It could certainly if you can read them in both ways, that then gives you license, if you wanted to simulate and reproduce *in silico*, these types of computations, it certainly allows you to replace heterodyin channels, heterodyning cycles, bumper tractors, receptive fields, of this type with a discrete representation.

And, to me, practically, that would be an important way to proceed, that simply because that minimizes the complexity of the generative model, and in minimizing the complexity, maximize the model evidence. So I don't know whether being Eurocentric is a good thing or a bad thing. Interesting to think about what is a self organizing map? So when I was at school, it was basically a couple map lattice with lateral inhibition to do this carving up the segregate, various populations, or localities from other localities. So if that's the case, again, you've got this notion of lateral inhibition, when it take all dynamics. What is that? One is that a statement of this exclusion principle, and, beyond simply the exclusion principles, I can't be in one place at any one time. But the fundamental exclusion that you get when dealing with discrete state spaces, I've got to be in this state, and I'm not in any other state. And that means that being in this state means, I have to inhibit being in any other state, to get a sum to one constraint.

So just by going, discrete, you're naturally inducing a by physical architecture, and that requires the lateral inhibition that is one of the defining features of a self organizing map. So that might be a virtue, of being a bit Eurocentric in the sense of understanding evolution, as working its way to a coarse grained, minimally complex discretized symbolic representation of the world. And then we just now read receptive fields in a slightly, we over interpret them, they're basically encodings, the world to be in this state, from my point of view. There'll be people chasing you are on there. So I'm thinking about Bruno self organizing maps, and Adam and Matt as well, there's a slow realization that these architectures are the way to go. That's coming out of machine learning, when people are getting bored with backpropagation. So they're now all turning to local energy based rules. And then I realized that they get much better performance from a deep neural network, if they just use a local energy based rule. And what would that look like? It would look exactly like the self organizing maps, all three we've been talking about, it's just me my, Not trying to please everybody else around me. And doing so, by minimizing my local variation, free energy or minimizing the prediction errors, mathematically, those been equivalent, the twist here is that this can be applied too effectively overly expressive, a amorphous a completely connected neural network. and it will still work with the right kind of pruning, you will start to get to the nice hierarchical structures that Bruno was showing, or with the right temporal scheduling, you'll get to the nice tonic and bound machines.

But at the end of the day, they're deep networks or even deep networks with a local energy. And those things I've now noticed, certainly in the University of Oxford, are now called predictive coding. So necessarily there's no prediction in the temporal sense that Adam was trying to emphasize, or in the sense of a Kalman filter, it's that they rely upon the local computation of prediction errors to generate the local energy function. So I see you're the people, the reactionaries in deep learning, the Young Turks who want to do better. They've all now identified predictive coding as the rhetoric in order to say, this is how it's done. And it's just a statement. You don't need to do. Bruna had a nice phrase or perhaps it was Francois, **“diffuse, you're learning everywhere through back propagation”**. And if it's working properly, you should be able to do it locally with your own little node, vertex, Sol, or GM, and enjoy Francois.

Daniel Friedman: If I could build on that, and then anyone else you'd like to add, a challenge that exists. And it's recognized in robotics, and many of the presentations brought up was how to move from continuous and high dimensional data, like high resolution video camera, or multi sensor integration in the world, eventually, towards logical and conditional contextual action. And so when we see the neural network representations, we see sometimes zooming in and zooming out and different ways that people are training those models, including limitations in those models training like the backpropagation, that Karl mentioned, as well as that Steven Grossberg has gone into. And so trying to contextualize that issue, in light of what we're discussing about discrete time and about symbolic logic, it seems that through the partially observable framework, not even saying the partially observable Markovian framework, but here including holographic principle, and so on, there's a way to move from a continuous statistical distribution, and make a map to a discrete statistical distribution, like the A matrix in the PMDPs that we use, can have a continuous variable and then map that onto a discrete statistical distribution. And then I wondered if there is something like a logical A, another tale of two densities, tale of two different cities or a third city. And so this matrix recognizes logic from discrete distributions. That's the recognition density. And then the generative density is the emission of logics that are compatible with discrete distributions.

Because with the recognition direction, recognizing conditional logics, and searching over relatively small sets of possible conditional logics from discrete distributions is possible, like a verb is never used. Two verbs in a row are not used, or something like that, from a discrete distribution logic can be extracted or recognized. And then, if there's a discrete distribution or more logics can be sampled. And that speaks to that inductive bias, where you want the inductive bias to have limited false positives and false negatives with respect to the empirical world. You wouldn't want to waste time spitting out logics, that cannot be, however, that might not be lethal, but it certainly wastes a lot of time. And then conversely, what could be lethal would be to have an inductive bias that fails to recognize empirical aspects of the world. And so that is, like an expectation maximization, but transposing not between continuous into discrete statistical space, but rather between a statistical and a logical space. So Jakub, or Bruno, anyone who'd like to add to that?

Jakub Smekal: I had some general questions that are related to Daniel's remark on the move between the purely continuous and statistical representation of the generative models into the discrete and since this week, I've been reading the paper from Chris fields and Karl and others on the FTP and neuromorphic development, I'm wondering whether the question of structure learning can be solved by some fundamental computations that are available at the very low dimensional level of quantum systems were given, the right environment, that system would naturally evolved into some discrete morphology, that it didn't start with similar, to the primordial swap then evolving into discrete or more discrete life forms. And whether that might impose the necessary structural guiding principles or message passing, where each new layer that evolves in the hierarchy is receiving observations from the other ones, given by the new Markov blankin that's drawn around it. But then, in terms of actual implementation, I am wondering whether that requires quantum computers or whether that can be done with some kind of different architecture that is able to have this automatic evolution in its morphology.

Bruno Lara: To round up what you were all concerned about. We were thinking and remembering this, ongoing back sums. And there is this proposal, some sums, but I don't remember the author's now. But it's this other type of architecture that takes into consideration the learning progress. So previous activations, and some history of the winning, previous winning notes, and so on. That might be the next step, so that you can actually monitor what's happening over time. And if you have one of these at least coding for error, then that would include the monitoring of the prediction error. And it would close this gap between continuous and discrete representations. Because then you could have it all over time. So I if you want that, I can send you some literature on that.

Daniel Friedman: Thank you, Bruno. One point on the morphological computational angle, Jackub, and then again, anyone can raise their hand, I thought about a bunch of tree seeds. We're back in frequentism again, so everyone can take a breath. But there's 100 seeds that are planted. And depending on the priors, inherited from evolution, and that updates which are happening from the generative process from the niche, there's going to be like a distribution of that tree through time. So like a palm tree is going to have a very narrow cone, some type of distributional cone across those 100 that are sampling from it. And then another shrub might have a difference shape. Then you brought up how potentially quantum or discrete morphological decisions could realize that continuous probability distribution at the population or even at the multiple worlds level. And there's something there also with the local computation of large models, that Karl mentioned, that it's something happens, where there is not even just a symbolic or a discrete decision that's made.

There's an embedded decision that's being made, that now is part of the history. And so the branching pattern of any given palm tree is going to be unique or any given shrub, yet they also may fill out at the population level, a distribution set that has these aspects that can be modeled as like a Gaussian Blur over tree morphologies, yet of course, no one is saying that the tree is a blur. And so there's so many interesting contrasts with the realized trajectory of the Lego robot. And that's the N equals one, the population of trajectories the imagined two set of trajectories. So having a unified ontology, to be able to talk and have formal, concise connections amongst these different remembered, now casted, anticipated or imagined futures, helps find the patterns across systems that, like Adam said, are essentially the basis of sensemaking and insight.

Adam Safron: I got to ramble. In terms of this, motion from our continuous to a discrete regime, or even drawing analogies from a quantum to a more classical regime. There's, in general, with respect to computational models of consciousness wondering, how a seemingly classical world of experience can emerge from a probabilistic model. Like, why are things so precise? And Karl has written some really interesting papers with Andy Clark on this, on the Bayesian blurb problem, and one of the suggestions was that, the discretization, for the sake of action, in order to act, you have to act in a particular way. And it's the requirements of doing a particular thing at a particular time induces this. And so one of the things and so this is competing, but in some ways competes for a suggestion, I had all those things compatible, because I was wondering whether basically, something about the timescales at which you can get, these coherent Eigen modes, or the population activity could achieve these, the timescales of the formation of these large scale attractors could create an in and out, of who gets to inform or not, and this could help to sharpen things up. And creating these population level attractors. But there's another way of describing in terms of what lets you act. So along those lines, I've talked to some Rodin researchers. And when you remove the hippocampus, you'll still actually get, roughly theta, stale, large mesoscale organization of brain dynamics, for the rest of the rodent’s nervous system.

So it might be an obvious it's, like degenerate, but it's natural selection, any mode, any way it could catalyze things to help with the coordination, to help with the alignment, the spatial temporal alignment that the cloud for different forms of synchronization was utilized. So you could get, for instance, a good amount of disposition, potentially from learning and interacting with the world that requires you to do this physically to interface with it. You get some of it from the overall Kinect Tomic properties that's what's required for the overall brain, to form attractors, the formula at a certain time scale and different nervous systems of different size and complexity with different information bottlenecks, might tend to form these attractive states roughly on that same scale, and maybe things are tuned for that.

Or maybe they get tuned by experience, either as an inductive bias or as an empirical, meta prior learning, or learned. You'd also get with things like the local logic of how you transition between these different equilibrium points for highly central structures. And so something that is very unclear to me. It's the extent I imagined the answer is like all of the above. And most combinations, but to what degree were these inductive biases are taking the form of evolutionary priors? And to what degree are the developmental priors? This is still very unclear to me. But one thing that there seems to be a tension in machine learning into under these, you want these rich inductive priors to do efficient inference and learning, because otherwise it's hopeless. But you pay a price in terms of generalization sometimes. And so I have no idea how nature balance this, to what extent, in what cases, I have some idea, but not nearly enough to feel comfortable. So I suppose that's my ramble.

Daniel Friedman: We can actually hinge on this and bring it to an area that some of the registrants brought up. And also something probably many of us have been thinking about, which is multi agent modeling. And I wanted to connect that to what Adam was saying, about what is granted, via embeddedness, what arises or becomes more possible simply as a function of realized Corporal embodiments as opposed to *in silico* simulation. And in our multi agent discussions, we've been differentiating spatial, multi agent scenarios from essentially non spatial, like digital or cognitive. So in the spatial multi agent case, the real world the niche, the generative process, does the work of inducing or preventing collisions, it cannot be the case that two entities are in the same location. Whereas in the cognitive case, whether it's Birdsong, or a negotiation, or verbal communication or visiting websites, we can both be at the same website. And so then there's sort of a mass parallel stigma occurring, or a mass parallel real time architecture, where there is some coordination. But the coordination isn't exclusionary, again, because two entities could, their thought trains could essentially cross in and out. And those trains are like ghost trains that don't exclude each other, whereas that couldn't happen in the real world. So I wanted to ask anyone who had thoughts, how does multi agent modeling come into play for robotics? What current issues are facing multi agent robotics? And how can what we're discussing here with active inference play a role specifically in understanding complex multi agent scenarios?

JF Cloutier: I have a question in that regard for Matt, your solutions been applied to a single agent? Do you see the possibility of a homeostat that is composed of multiple agents that will direct their collaboration towards achieving a common goal? Does it scale to multi agent situations?

Karl Friston: I will answer for him, I would imagine, what he would say is if you take the generalized synchrony perspective on with the emergent properties of it, start coupled to its environment, and you coupled to homing stats together, they will find a mutual homeostasis, that will be a joint synchronization manifold. So what you'd expect to see is coming together exactly. In the spirit of dynamical generalized synchronization. So as Daniel mentioned earlier on, though, the homeostats will be singing from the same hymn sheet under the constraints of what they can communicate. So from Matt's point of view, he's more interested though, in establishing a generalized synchrony between a use case and industrial use case. And he's hoping it's done, as opposed to letting to get stats, shape and design their own little eco notion. Indulgent of some cultural niche construction. While I'm talking, though, something very interesting about Daniel's question in relation to teamwork. I sort of overheard the little robots telling each other what they were thinking, I thought that was really important. And simply because you're speaking to this general question about, what does active inference or what are the spatial considerations that you might want to bring to the table when thinking about a multi agent setting? I think there are two ways we could talk about agent about this. First of all, it's having the law of requisite variety across agents.

And then the story would unfold in terms of natural selections based on modern selection. I think answering large parts of Adams questions about where the inductive biases come from. If you cast the biases as selection biases, we're talking about Bayesian model selection, selection along amongst what the requisite varieties afforded by Ashby's law. To make that Bayesian Model selection work, you have to have natural selection. So there is a great story about the importance of multiple agents, from the point of view of structural learning, for free, as an emergent property of natural Bayesian model selection, or natural structural learning. And then the other thing is, from the point of view of active inference, if you've got multiple agents, what's to stop you thinking about these multiple agents as, one big agent, where you've cut some message passing between them. And one big agent, with lots and lots of eyes and sensors on it.

So I'm asking now, when I looked at Karla, and Andy, what's to stop me thinking about Karla and Andy as one agent, that has a really flexible and deployable set of sensors. So they've got eyes that can point in different directions. So if we translated this into controlling drones, for example, and we have a swarm of drones, we can think about that as one agent, one robot with lots of deployable eyes, which gives you an enormous flexibility over the possibly complexity of the way that we control our two eyes, which are both in front of our heads. So how would you then write down a good generative model for a swarm of eyes, where there's one CPU, there's one, the Lego brick at controlling all the drones. Well, you try to judge the model with multiple sensory modalities, where you needed to deploy action in the right way to get the right epistemic foraging or whatever. But that would entail now, message passing, belief updating, lateral interactions between the brains of agents say, you can't do that, you've actually got to have physically separable robots to have a multi agent setup. So how can you now work around the fact, you don't have direct message passing and belief updating between the brains, the separated brains, when you just have communication? So provided you broadcast what you believe, and provided those beliefs are perspective independent, so they're conserved from what I say in terms of my frame of reference, is meaningful from your point of frame of reference, which, incidentally, for Daniel and Jakob becomes relevant from point of view of quantum frames of reference here. But if we can assume we've all got a allocentric frame of reference, then all of those required to put together the many brains into one brain, is to have beliefs broadcast, those beliefs that are conserved or shared in the the ensembles Jyoti model. So I don't know, where was Karla able to hear Andy and vice versa. So what did they actually share a narrative of their belief updating?

JF Cloutier: No, they did not. The talking was mostly for my benefit. So I could see what was going on in their mind at the time. So when when Karl was saying, Andy is freaking out, I knew that the chain of model had identified the behavior and inferred the mindset of the other robot, but I am playing with the idea that they can communicate by just distributed message passing from one robot to the other. I would consider one agent as a source of sensation for another agent, in the same way that internally generative models, the beliefs of a general model becomes the sensation of another or a higher level generative model, that can scale across multiple agents. And that would happen by communicating these predictions across agents and these prediction errors across agent as they propagate between journals within single agent and scale of the architecture. So instead of having a society of mind within an agent, which will also have a society of minds across agent and the same mechanisms will be at play. But you're absolutely right, we will need to have this communication, but it will be the same kind of communication across society of minds, as they would be within a society of minds. I'm hoping that it would be self similar. And the same architecture would apply at in scam.

Karl Friston: It actually speaks to Jakob question about your backup, like is a Markov Blanket of nuts past you get from that scale, free separation and refined minimally complex message passing. There's something quite fundamental there about the nature of communities and the scale of the world in which we live and all the organs that comprise be living in that world, that scale free aspect, that is defined by the sparsity and the absence of coupling and getting the messages that are communicated right, something quite fundamental.

Adam Safron: I'm wondering, so to what degree do you get common agency for societies of minds due to common embodiment, but when we're going for a common, or joint agency, and maybe even different forms of joint identification or D, individuation Or re individuation of individuals into a collective. To what degree do we need something as constraining as a joint embodiment, for instance, I'm thinking of as soldiers marching in the ways in which we seem to potentially even expand and hack our body and maps by sharing, different synchronous modes, that literature is somewhat contested. You don't need to have that synchrony though. It's a strong enough shared task, is enough to make the central thing, their role of where they're singing the hymn sheet that becomes a primary attractor governing them. And you don't need to, necessarily have this physicality, Think of the different means in which you need something like synchronous in time or is it just a very strong selective pressure for coordination to establish a synchronization manifold to pull off the RE individuation.

Daniel Friedman: This ties to JF Cloutier framing of society of mind. And then we can contrast that with a society of bodies. So the Society of mind is that virtualized case, whether it's the counterfactual virtualizations, that cognitive entities can be modeled as doing or whether it might even be a society of minds in a digital setting. And then there's the societies of bodies, which maps earlier to our multi agent discussion on a physical crowd. So what are the similarities and differences with the digital swarm and the physical one, it comes down a lot to their ability to collide. And again, the digital swarm can weave in and out because they can coexist in the same location in a semantic space in that generalized forging way, whereas the embodied swarm is going to have collision prevention by virtue of the physicality. And by using active inference to study these systems and integrate them, we do approach exactly what you brought up Adam, which is almost what do we get through shared task? As opposed to what do we get from a common task, something that we merely have in common, versus something that we're actively coordinating on together?

And potentially even coordinating together in the same exact space or on the same instance of, which provides the most constraints, the people are rowing the same boat versus rowing parallel boats versus on different lake. So as we separate spatially, and especially virtualize, there becomes more and more possibilities, and for those who are coming for perhaps from a robotics angle, and wanting to understand what active inference brings to the picture here, hopefully we've pointed a few things like the scale free or scale friendly nature, of models to be composed based upon their sparsity and define interfaces, and also the multimodal aspect. For example, Karl, asked JF, if the audio could be hurt, rather than only emitted. And that's not going to require some bolted on, communication module is going to be able in the symbolic or in the numerical case, to be mapped onto an architecture that also Bruno showed, these architectures that can do sensor integration as a function of the interface definitions locally, rather than potentially have ad hoc structural design decisions, that could result in a lot of research and engineering debt. So have you here any thoughts on that?

Bruno Lara: I come from an old fashioned school but as you can see, in our implementations, they are very low level and coming from the sensory interaction with the world. That is why we haven't been so far very concerned with very high level representations known. So we're dealing with very basic interaction with the world. And at the same time, it's very interesting, this interaction between agents and so on. But I've always thought that, first, we need an agent that nodes tells in the world and has its own model. So a first frontier or a first blanket, as you like to call them. And only then can start to understand other agents and to interact with other agents.

Karl Friston: There is an argument from developmental neuro Robotics to have a true sense of self, you've got to have a true sense of other and you can only ever have a true sense of other. If there's something else out there. That's not physically very much like you. So speaking now to Adams, point near, or Daniels question, that the shared body as opposed to the shared narrative there is an argument, I'm not making the argument, I'm just saying that could be an argument in order to disambiguate the causes of some sensory consequences of an action, where the action could have been made by you, or an identical robot, or me or mum, or me or my brother. That is the only case in which you are now going to be a need to contextualize and assign and attribute the agency of this outcome, to what to self versus other. In a world in which I was the only object or phenotype like me, I would need a sense of self and I wouldn't need a sense of other, it's just when you have multiple agents that are quite similar and confusable then you actually need a sense of self, to make sure it's not into you and not me, which of course, speaks to not only theory of mind, but the essence of communication as well. So I'm making that point that the putting two robots together, may be as you point out, once you've sorted out, a robot just learning how to move then learning the consequences of it moving, which could actually be reproduced by somebody else. And then it might develop a sense of selfhood or minimal sense of selfhood. And then you're in the game of truth theory of mind.

Daniel Friedman: It's very interesting area with thinking through other minds, as have been brought up in some of the presentations. And then society of mind is that nesting of blankets of different kinds of generative models, but again, using the same statistical or formal machinery, as we could have a nested multi level regression model, where one model was in kilometers. And then there was another model that was in degrees for temperature. And also, the question about swarms and collectives and groups, comes up in biology all the time, with different ways that people delimit or qualify individuality, ranging from the evolutionary unit of replication, the Kantian concept of an organism, as the unit that is teleologically closed, the physiological individuality, which might even include cases like symbioses, the information theory of individuality, and different ways that we can look at information processing and transfer, in terms of what individuals are. And it's so fascinating how that comes into play with robotics, where when we think about the robots that will be interacting with us, as a slightly different set than the ones that might be working underwater on a pipeline.

Like Matt showed, they might be able to interact with a relatively simple generative process that doesn't exhibit mind like qualities. It's interacting with a mere active inference entity. But when on the other side of the blanket, there's another adaptive act of inference entity, and especially when it's us, then there's a space of norms, and also loss, which are that pseudo code execution order for thinking through other minds in a way, how will robots navigate a space? And how will they be able to make abduction occur in a real time way, both in the generation of novel hypotheses with inductive bias, followed by the selection of trajectories of action, again, taking into account formal codified law, as well as the state of exception even, or understanding, when preferences allow for something to be so strongly desired, that how and when it's a pursued, might not be how you'd pursue it in a different time. So there's a lot of cool threads, Adam or anyone else.

Adam Safron: This is reminding me also from the first session, there was mentioned a value alignment. And this seems to be a multiscale problem, in terms of, it will show up as much as the robot not stepping on your toes, or crashing your foot to as it expands as is it optimizing in the direction, or its tensors going in the direction that you want your tensors to go, shaping? And it seems like of the proposals, sometimes there's begged questions that active inference, maybe answers. So it's a framework like cooperative inverse reinforcement learning. And so you are trying to roughly optimize for the utility function of the other agent. So how do you get this share utility, but then act of inference models, where you're bootstrapping minds, intersubjectively you have regimes of joint attention and thinking through other minds or in some of this work with them. I'm doing with Anna chinito. She emphasizes how we start out, actually physically inside of another organism completely dependent, homeostatically. And so you're automatically grandmothering in this joint intention right from the get go. And the seeds of organization and individuation are already scaffolded in that way, by the niche contextualization, where you're co constructing each other as your mutual niche construction. I don't know what point these problems deploying robots when they first center because, it's argued always highfalutin as like intelligence explosions go a recursively amplifying system stay alive dual but in the world, how can I make sure the robot doesn't crush my foot? So the ways in which co valuing and the robot identify yourself as an individual relative to other individuals plays into it. It seems active inference has a very rich way of handling and modeling a lot of these different proposals and processes. But something I was wondering to ask actual roboticists, how near term is it a live problem of getting? What forms of social modeling for robots? And what forms of a sense of self modeling for the robot? How much do we need at what stage for what levels of deployment in the world? With what degrees of robustness?

Daniel Friedman: Great question. And maybe to double on what active inference does to potentially frame that junction, since in this roundtable, you address but this is the stuff and substance of applied active inference symposia for many years to come in, an economic framework, reward absolutist framework, which is a full stack, ranging from the ways that models are trained based upon pragmatic value and reward, all the way up through a world that values economic returns. In human robot alignment, or in multi agent alignment, or generally the question becomes, how are we creating and then allocating pragmatic value and epistemic can be valued to the extent that through time it provides pragmatic value. For example, one person doing a little bit more of a research angle and one doing more of an application and profit side of the business. And when we shift to an uncertainty imperative, for a sustainable or even optimistic world model, then we can achieve pragmatic value as a consequence of a process theory that highlights reduction of uncertainty. And then the question moves from creating and allocating value to how can this ecosystem of diverse entities find a general synchrony and communicate and be how they are, in a way that will be reducing the expected free energy of the ensemble. Which is not the question that was even approached by the create value, allocate value framing that has come up in AI and continues to occur to this day? What if the image creators, what if they end up reducing our food allocation, so they take the intellectual property instead of providing it to humans? That might be framed slightly differently in an uncertainty reduction framework plus optimism rather than in a reward maximization, which somewhat enforces an atomism and even a pessimism.

Karl Friston: I wanted to agree with you. That was an excellent point. There are so many ways you can tackle that I'm still puzzling over out of charge. How do you stop robots standing on your foot? As how do you stop little puppy dogs peeing on the carpet? It's really going to train them. I don't think there's any magic answer. The answer is what Daniel said, things are designed and can presumably only exist under the free energy principle, if they minimize their uncertainty or expected surprise, so that they make everything as predictable as possible, which simply means that if I'm living in a world full of dogs, robots, cats of flies, and plants, then we're all trying to make ourselves as predictable as possible to each other. And that is the folk psychological way of saying that variational free energy has an extensive quantity. So if a set of Markov blankets or phenotypes of varying forms and structures jointly has its own Markov blanket, so it is an ensemble or a group or a community or a family, then it must put an upper bound on its surprise and free energy. Because the free energy of each constituent of that ensemble is so summed to give the joint free energy, then it also requires that each individual is trying to minimize her surprise at the same time, it's all internally consistent quite, to my mind and magical. If you just look at it in terms of minimizing surprise under optimism, was telling all that supported? You'd have to make you dog surprised when he wheeze, so you've got to find a way of making robots surprised when it stands on your foot.

Daniel Friedman: JF, you have a dog, right?

Karl Friston: Yes, I do.

Daniel Friedman: So how to see similarities and differences with these versions and also potentially even a family. So how do you see these different entities being communicating and and behaving appropriately or not and learning?

JF Cloutier: Well as having a dog, it raises the question of, Do I make myself understood? That's a very difficult question to answer. When I say no, you're not allowed to eat on that plate on the table. I think my dog understands, I'm not allowed to do this. Now. As soon as I walk out, then permission is granted. So communication, it's very difficult across individuals, especially across species. But I want to rant a little bit on scale free nature of free energy principle, the fact that it can apply at a societal level, the same way that it applies, as a Russian doll, to the sailor level. As a software developer, I see self similarity, recursion, and fractal as a beautiful thing. And the same way physicists have symmetries as a guide to what is right, because it's beautiful. We share self-similarity as a guide, as well as beautiful, and possibly true. And self similarity is beautiful. Because it's collapses, the amount of information that you need to generate something rich. So that's why having a society of mind made up of actors and having a society of minds and having the same principles scale up. Feels very beautiful and feels right.

Daniel Friedman: If we could go for any length of time, a final set of thoughts and reflections from each of you.

Adam Safron: Quick, interjection. JF Cloutier, if you have anything written on that, or want to write it, there's an upcoming spatial issue on symmetries that it might fit with.

Daniel Friedman: Would you like to give any final reflections or anything that you've heard, or felt updated by any thoughts you have on the state of the applied active inference, in 2022, in robotics, or wherever we're heading? Now, this symposium is behind us. I'll start with Adam, but then everyone else can go.

Adam Safron: Thank you, Daniel. Well, this simulated a lot of questions and seeing the range of work being done was inspiring. And all I have to say is, I was grateful to be a part of this. Thank you for putting this together.

Bruno Lara: Thank a lot for the invitation. It was it was very kind of you. I want to thank Mark for insisting Mark Miller that was insisting on us to present with you here. It was a very nice experienced and well, we keep working. We need more hands. We have more ideas than hands, but I suppose that's everyone's problem.

JF Cloutier: Well, again, thank you very much. This was an extremely stimulating every talk, I came up, I came out of listening to this, I want to introduce in my robots, some aspect of it. And my mind is buzzing right now with possibilities. And so thank you so much for this opportunity.

Jakub Smekal: Also, thanks a lot for being able to join this final round table. And for all the great presentations, I'll definitely have to look over them probably a couple more times, to fully understand all the progress that has been made. And specifically there's a lot to consider on the multi agent modeling and the ideas in this discussion that we were also talking about quite a lot, in the active blog friends project. Probably was left with more questions at the end of it. But that's also the exciting part of it. So thanks a lot.

Karl Friston: Thank you so much to Daniel and his colleagues, but personally to Daniel, thanks so much for all your energy, not just today, but over the years is really great to see these people and colleagues come together and generate ideas and questions, which is exactly what we need to do. Thank you.

Daniel Friedman: Thanks a lot, Karl. And by one personal reflection, it swooped in at the end, when JF said that. From each of the presentations, there was like a module or an archetype or a function that transposed. And that is proof of concept of working in a shared ontology, as well as in an embodied shared ontology, which is to say, a field and a community of practice, with different small world's structures and so on. But when we have the ability to transpose across systems and scales, then we can bring in the modules and the pieces that people are mentioning, and start to understand how those functions can be composed and designed. And that's extremely exciting. Everyone, thanks for joining the roundtable, you can depart the zoom or I'm just going to review the presenters again and the CO organizers. So thank you for joining the roundtable.

SYMPOSIUM OUTRO: In the first sessions. There was **Tim Schneider** with "Active inference for robotic manipulation", **Tim Verbelen** "Robots modeling the world from pixels using deep active inference", **Ben White**, "Artificial empathy, active inference and collective intelligence", **Noor Sajid** "Learning agent preferences" and **Wen-Hua Chen** "Dual control for exploitation and exploration and its applications in robotic autonomous search". Then, in the first roundtable, it was Wen Hua and I, talking about dual control.

The second session began with **Bruno Lara**, "With prediction aerodynamics, a proof of concept implementation", **Matt Brown** "Real time robotic control through embodied homeostatic feedback". And **Adam Safron** with "Generalized simultaneous localization and mapping as unification framework for natural and artificial intelligences towards reverse engineering", the hippocampus and to rhino system and principles of high level cognition. And then **JF Cloutier** "Towards a symbolic implementation of active inference for lego robots". We've just completed the second roundtable with Adam Bruno, JF Cloutier, Karl, Jakub Smekal and I, the organizers for the symposium were Mark Miller, Matt Brown, Blue Knight, Alex Vyatkin, Ivan Metalkin, and myself. So thanks again. Till Symposium number three of applied Active Inference, we hope to see everyone around the Institute, bye.