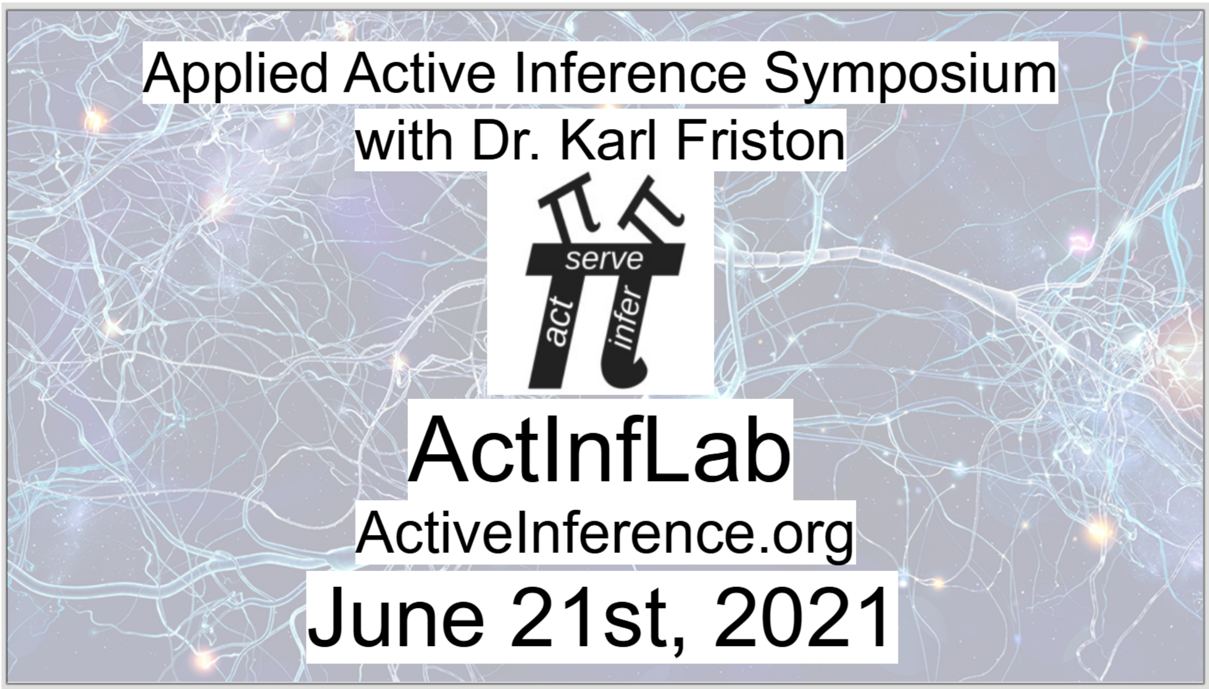
Prof. Karl Friston, Applied Active Inference Symposium, June 21, 2021



Abstract:

On June 21st, 2021, Active Inference Lab (activeinference.org/) hosted its first Applied Active Inference Symposium, featuring Professor Karl Friston. The Symposium was structured in three sections, corresponding to the Organizational Units of the Active Inference Lab: Education, Communication, and Tools. This publication reflects an edited and enriched transcript of the proceedings of the Symposium.

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Video Sections & Links:

- Part 1: Education (.edu), page 3, youtube.com/watch?v=INRaCBikpso
- Part 2: Communication (.comms), page 27, youtube.com/watch?v=X2GwqUVLlcs
- Part 3: Tools (.tools), page 47, youtube.com/watch?v=hW9IiOujS1E

Active Inference Lab

Active Inference Lab (ActInfLab) is a non-profit organization that is a participatory open-science laboratory curating and developing applications related to the Active Inference framework.

The goal of ActInfLab is to produce cutting-edge research and enable real-world applications of Active Inference.

ActInfLab also seeks to scaffold the Active Inference community: increasing the competency of participants & raising broader awareness of these topics.

ActInfLab consists of multiple organizational units (Education, Communication, Tools), each with specific affordances and functions.

We seek participation from:

- All who are curious about Active Inference and how they might increase their competency in this area.
- Individuals who seek to assist projects of various kinds through role-based participation, thus learning Active Inference by doing.
- Researchers who seek collaborations that apply Active Inference to their field or system of interest.
- Those who have mastered another domain (such as ontology, linguistics, machine learning, agent-based approaches, robotics, communications).
- Anyone looking to adapt and innovate through transdisciplinary research, generation of start ups, applications to industry, and more.

To reduce your uncertainty about ActInfLab affordances for participation, please get in touch with us through email: ActiveInference@gmail.com before or after completing our Participation form.

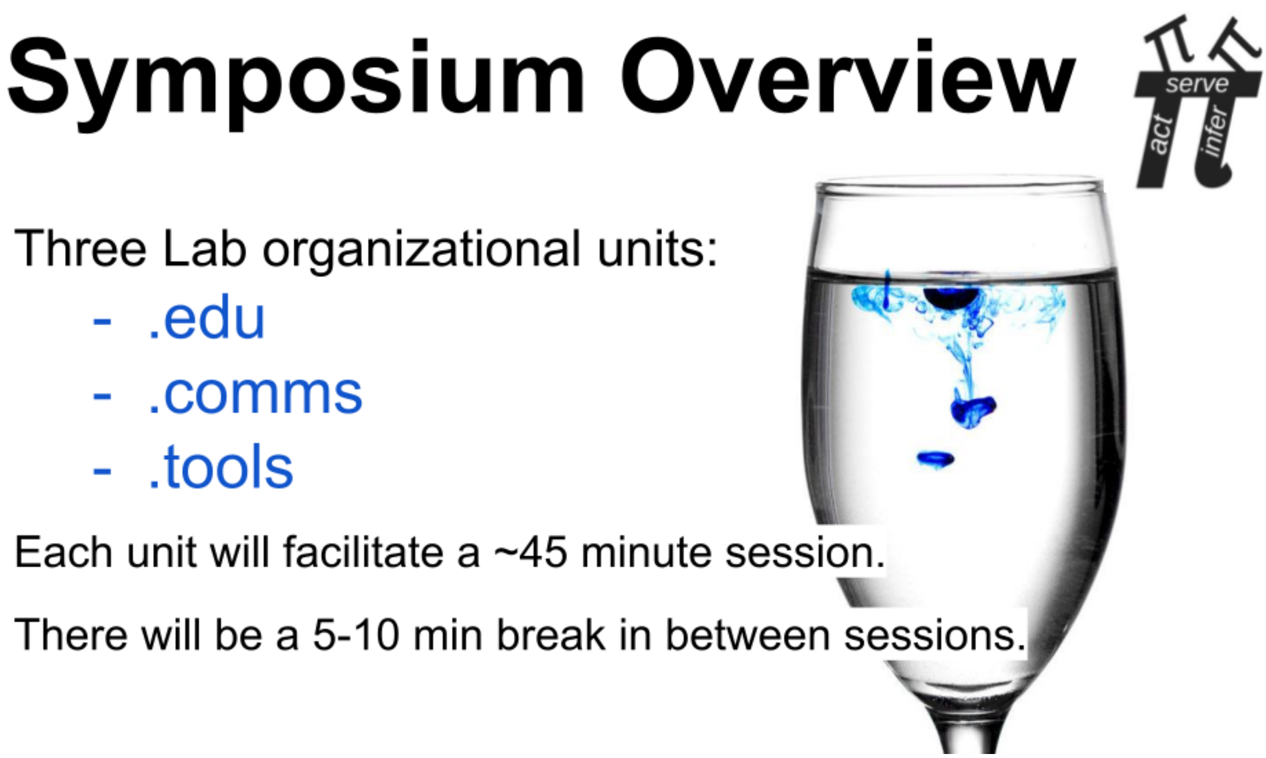
Session 1 (.edu), Introduction

00:01 *Friedman:*
Hello, and welcome to the **Active Inference Lab**, to our first-ever Applied Active Inference Symposium. Today it's June 21st, 2021; and we're very honored to be here with Professor Karl Friston, and many of our lab participants.

00:20 Just as a way of quick introduction, the Active Inference Lab is a non-profit organization that is a participatory open science laboratory. We're working to curate and develop applications related to the **Active Inference framework** -- something that, hopefully, we'll be going into a lot more in detail today. And this is a screenshot of our website [bottom of page 2].

00:45 As far as the overview of this symposium, there are three organizational units in the lab: .edu [education], .comms [communication], and .tools. And each of these units are going to facilitate a 45 minute or so session, and we'll have a short break in between sessions.

Lab organizational units: .edu, .comms, .tools:



In our weekly meetings over the past weeks, for each organizational unit, we've been developing questions and getting excited about things that we wanted to talk to you about, as far as a few overarching themes that were kind of spoken to, really through the whole journey of our Lab, but also across organizational units.

Theme 1. Applying Active Inference Across Systems

01:32 The first theme is *[1] Applying Active Inference across systems* (again something that will come up probably in all sections);

Theme 2. Research Debt

01:40 The idea of *[2]* ***Research Debt***, the idea that we don't want to be developing research frameworks that have a huge burden on those who are learning and applying; and that, especially early in the formalization of frameworks, it's extremely valuable to increase the accessibility, so that we don't end up with major headaches and incompatibilities later on;

Theme 3. Collective Intelligence

02:06 *[3] Collective intelligence* and the ways in which that is manifest across different systems;

Theme 4. Transdisciplinary Teams, Projects, Communities

02:12 *[4] Transdisciplinary teams, projects, and communities*, which are kind of like nested levels of organization (but transdisciplinarity is something that is necessary for the type of work that we're all interested in);

Theme 5. Challenges and Opportunities for Research

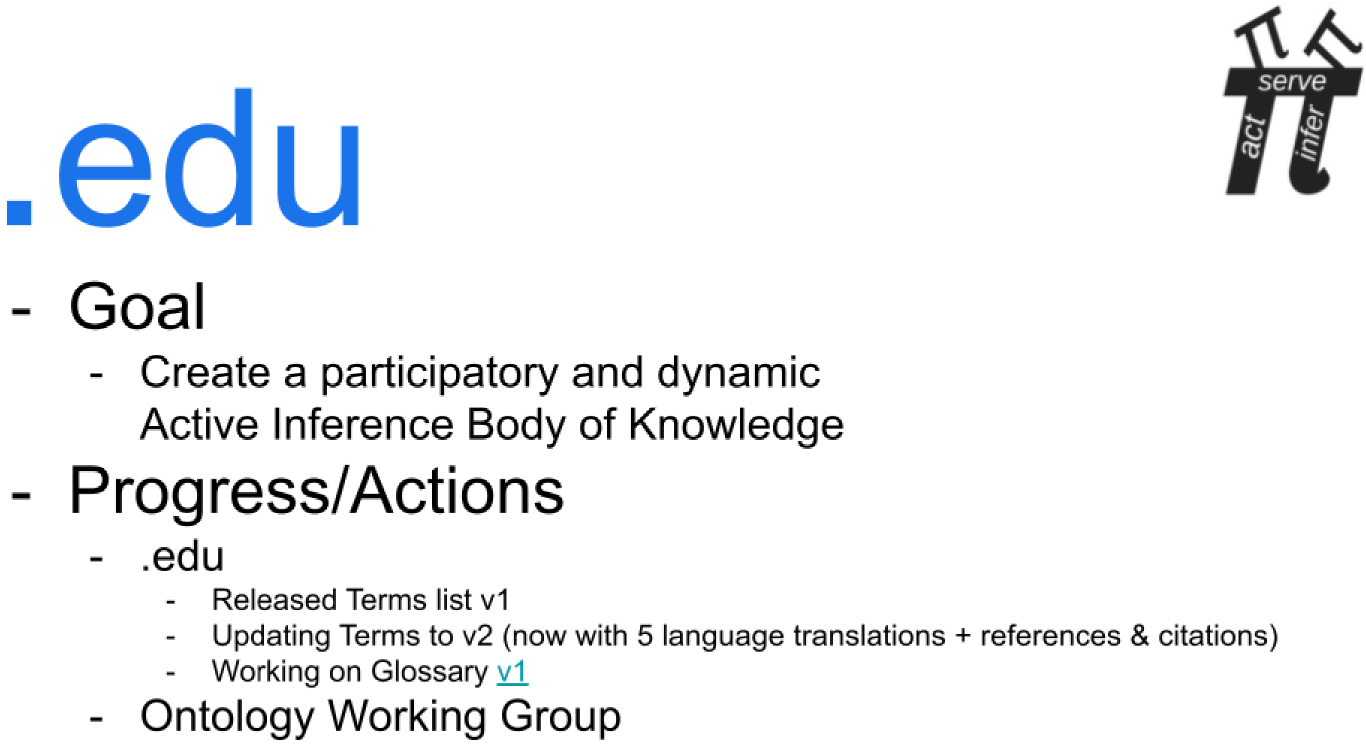
02:27 And also just modern *[5] Challenges and Opportunities for Research* and all that that means related to online and everything else;

And, of course, *[6] Anything else* that you have tumbling around, and wanted to bring to the table, thematically.

So there we are, with our sort of lab overview and introduction.

Session 1 (.edu), Education

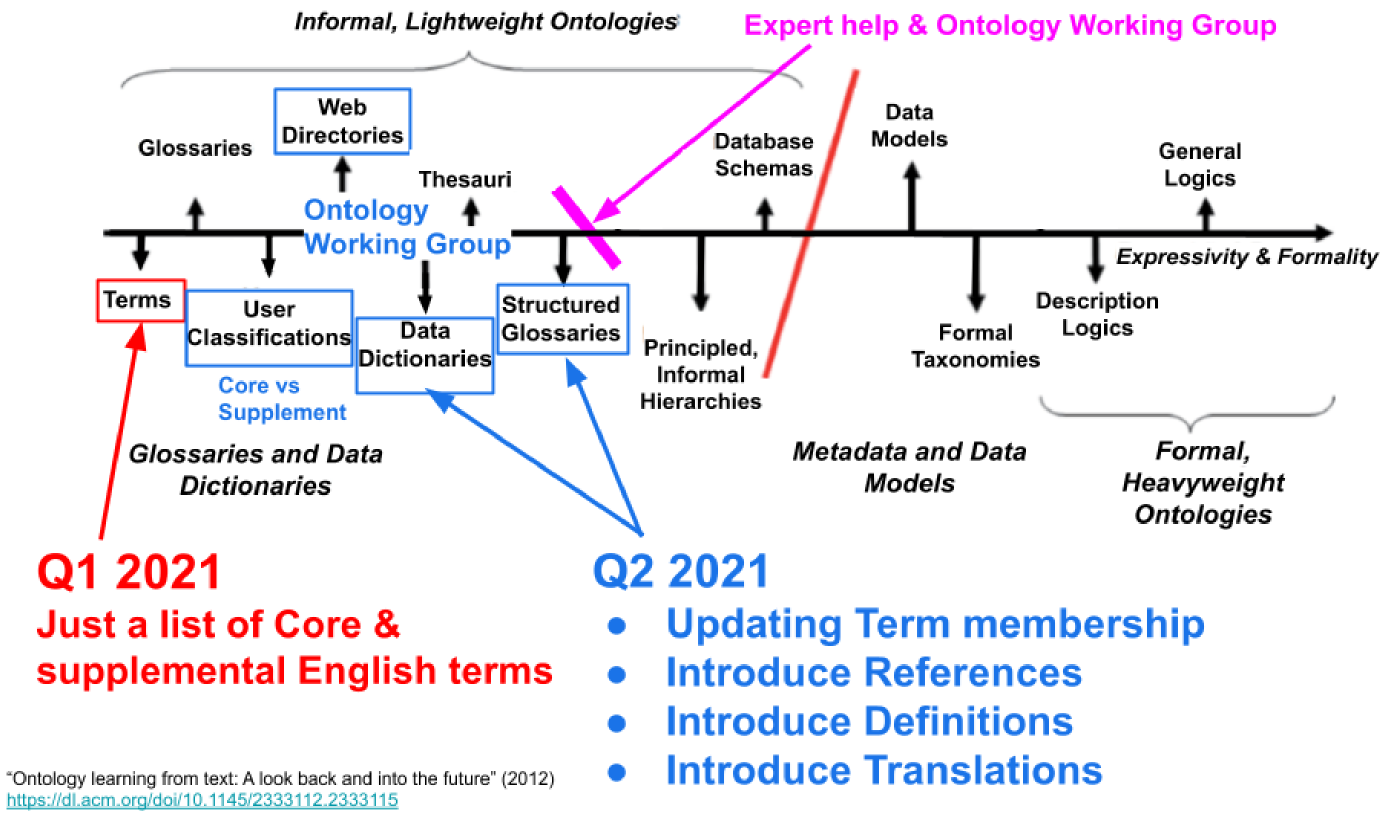
02:54 Let's go to our first organizational unit, *.edu*.



02:59 The *goal* of .edu is to scaffold and create a participatory and dynamic Active Inference Body of Knowledge, which we'll talk more about in a second.

Ontology Term-Development Timeline

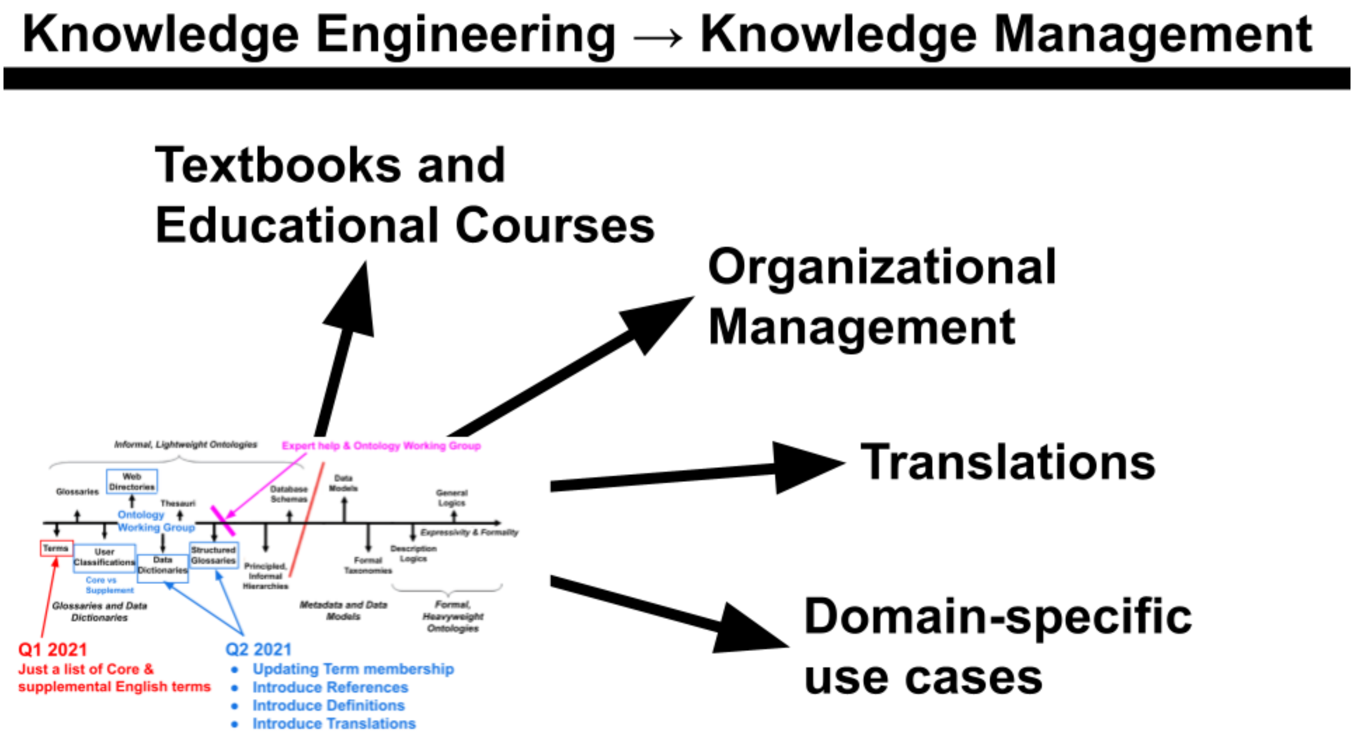
03:10 Our *progress and actions* this year have been to release a *terms list*, v1, which benefited greatly from your feedback. And also we're now updating the terms list to version 2, which now includes five complete *language translations* and many references and citations for the terms.



Wong, Wilson; Wei Liu; & Mohammed Bennamoun [Ontology learning from text: A look back and into the future](https://dl.acm.org/doi/10.1145/2333112.2333115) (2012)

03:34 The way that we're approaching the development of the terms is by using approaches that place **ontology**, and progressively more formalized versions of ontologies, as kind of the backbone of an educational **Body of Knowledge**.

So we started on the left side here, with a terms list in the first quarter of 2021. The Ontology Working Group is like a train that's pushing to the right, as they're learning ontology by doing, and developing progressively stronger and stronger ways of relating the terms and the concepts that are essential for understanding Active Inference. And this will help us develop principled educational material that's also able to be translated rapidly.



04:24 Alex, do you want to give a quick thought on where knowledge engineering comes into play?

04:33 *Vyatkin:*
Yes, thanks. At this slide, we are showing this work with ontology with a system engineering approach, which we are also using in the Lab; and considering possible deliverables of working on educational materials and creating them. We should have at some point of time textbooks and educational courses, and actually maybe this Lab is started from the idea that a textbook for Active Inference should be created. Also, we see some connections that can be applied to organizational management for creating translations and to make it multi-language from the beginning. And also we should look for some domain-specific use cases that we can understand in terms of that ontology that we are going to create.

05:35 *Friedman:*
Thanks, Alex. So on to the questions section. We're going to start off pretty broad here in the .edu:

.edu Question: 'How do we determine the core terms and ideas for Active Inference?'

05:45 How do we go about determining the core ideas and terms for Active Inference? This will be the format of the question slides, Karl, so feel free to jump in.

06:09 *Friston:*
Right! I guess it will be structured around the key ideas, and essentially ingredients that underwrite the Free Energy Principle, and how that translates into Active Inference. So, without thinking about it too deeply, my mind just goes to what are the things, what are the basic ingredients you need to explain to somebody, what Active Inference is, and why it works.

And it normally starts off with the notion of a **generative model**, and then from that, you spin off all the appropriate mathematical ideas and constructs and descriptions that would attend that. I mean it may be best to reflect the question back to you.

Role of a Formal Ontology

07:10 This is a really neat idea -- having an ontology! And it's certainly my experience that people are entertained by, sometimes the poetic use of phrases and descriptions, such as **epistemic affordance**, when trying to grapple with, "What are the fundamental ideas behind Active Inference?" Some of them are fundamental and some of them are not. So, it's certainly an interesting idea to try and tie down the ontology.

But let me ask you: This ontology just means what it says, in the sense that you're trying to define the essential concepts and how they relate to each other? Is that the basic idea?

07:57 *Friedman:*
Yep. Going back to this slide here, [shows Active Inference Working Ontology] we want to have a continuum from a list of terms, potentially, that could be developed into coherent and, again, principled course material and competencies; but also develop a **logic**. And we're developing within the **SUMO** ontology development framework, which defines not just relational edges, but an actual logic.

And so we hope to be able to ask, "Is this a complete Active Inference model? Have we really checked off all the boxes?" -- and used those kinds of logical tools that are accessible to the well-developed ontological frameworks.

08:41 *Friston:*
Okay. Well that's very compelling and very clear.

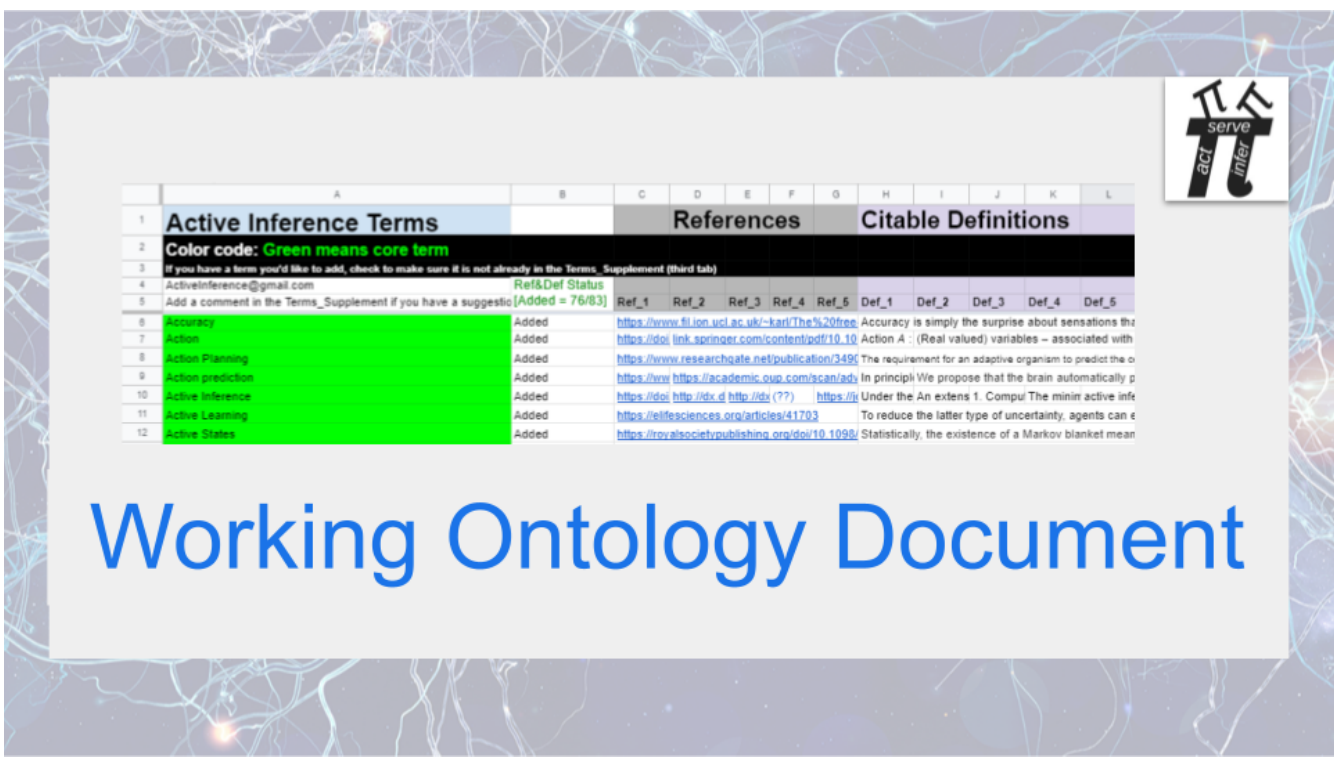
It strikes me then that it would be useful to **link** that operational ontology to the underlying maths.

Much of the conceptual steps, both in understanding and implementing Active Inference, (usually in terms of simulating your interesting behavior, or using it as an observation model to explain some empirical data from a study) -- much of it can be developed in terms of a series of moves that usually (or, in fact, almost universally) inherit from, are framed in terms of, either **information theory** or linear algebra or differential equations; and you can just build the story from that.

So, if you're looking for that degree of formal and useful detail, then one principle you might refer to is basically: "Where does one equality assertion or description or variable or object -- where does it come from in terms of inheriting from the more basic formalism?"

So, what I'm thinking of here is: "Where does Active Inference *start?* And how do you *get to* the calculus and the **Bayesian mechanics** that you'd associate with Active Inference?" And my guess is: given the structure or the way that you have approached the ontology, you've probably actually done that already or are in the process of doing that.

Are you going to go through some examples that would sort of highlight the strategy and the problems, which are usually more illuminating than the solutions that you've encountered so far?



10:49 *Friedman:*
Sure! I'll switch here to this screenshot of the current state of what it looks like.

And we're starting just in tabular form by compiling up to five references and citable definitions.

First just looking for exact cases where a term is used. And then we'll go from how the term *has* been used, towards synthetic definitions that capture different senses of the term.

And then along with the concise narrative of the field, and also ontology experts who are here with us, we're going to then be working to make the actual logical underpinnings, elucidated in terms of specifiable code, rather than just concise English definitions.

And then from that sort of generator of the formal relationships we'll be able to descend into mathematical formalisms, or other natural human languages.

11:48 *Friston:*
Yeah.

11:49 *Friedman:*
We'll keep you posted on this project though, for sure.

Let's go to this next question, and imagine that we had that set of terms in development (it's going to be a work in progress our whole lives):

.edu Question: 'How Do We Go from Core Terms and Ideas to Interactive and Enlivening Education?'

12:04 "How would we go from **core terms** and ideas, to an interactive and enlivening education that speaks to people from many different backgrounds?"

Aim at non-specialists.

12:18 *Friston:*
So, I'm going to answer this question from the point of view of my experience as a supervisor, which is probably a little bit of a narrow remit from your more general ambition. I imagine that this is related to this notion of -- (was it "research debt?") -- but this notion that you don't want to put too much pressure on people, when becoming acquainted with the utility and application of either the code or the ideas.

Build toy models

12:51 In my experience, in an academic setting, just having toy simulations is usually the best way to give people a feel for what this approach *does* and how it can be used. So, it's enormously potent in terms of demystifying and also illustrating the functionality at hand, or that can be accessed. Having a sort of a working, or at least a *toy*, model provides a proof of principle, and that can strip away the magic as well.

And, I think your ambition to try and make this accessible to people who are not necessarily fluent in the underlying information theory or **dynamical systems**, is very laudable and perfectly feasible. So, again, in my experience, some of the most creative applications of Active Inference can be by people who don't really necessarily wonder too much, "What's underneath the hood?"

Get the generative model right!

14:11 It all comes back again to the design of the generative model. So, if you get the generative model right, and it's apt to describe the thing that you want to understand or to simulate, then usually everything else follows suit.

And I mean that in the sense that you can just take off-the-shelf software, which I presume that your ultimate ambition is to make available, and make it work in the service of saying, well... "What would this **agent** (or this synthetic creature or person) *do* in exchange with her environment, *if* this was the generative model and this was the generative **process**?"

So, a lot of this really, I imagine -- in terms of answering your question -- "how do we go from core terms to interactive and enlivening education?" -- is just establishing a *language*, a **lexicon**, that allows you to talk through somebody in constructing their own simulations that speak to the issues, that engage them either academically, or beyond academia.

So, clearly then, the core terms play the role of literally a language, in terms of communication, which brings us back again to the importance of the ontology, and having the terms linked in a formal way to the mathematical expressions and also procedures and processes. So, I guess that a precondition to use the core terms in an interactive and enlivening, educative sense will rest upon getting that ontology right.

In my experience, you know, the best way to get the ontology right, in the sense of it being enabling, is just to talk about the terms, until there's some consensus and everybody understands them, both in terms of their teleology, but also in terms of where they come from -- from the point of view of the code and ultimately the maths that underwrites all this.

Is that the sort of answer you're looking for here, or thinking along with? Are you thinking along the same lines?

16:46 *Friedman:*
It sounds great. There's so many dimensions there!

Just to provide a summary, or just jump in at one place:

.edu Question: 'What is Active Inference? - - what does Active Inference do?

16:56 What is Active Inference, and what does Active Inference do?

17:03 *Friston:*
Right! That's perfect! - Because, I was just thinking: it would be really useful just to go down the terms that you had in the previous slide highlighted in green, because all the heavy lifting here is really just shouting about, what are the core aspects and claims, or the core things that you're trying to communicate with any one of those terms.

So, for me, Active Inference would be a description of a process that can be seen as something that arises from the Free Energy Principle. So you can either tell that story from the point of view of a physicist, and say that Active Inference is a **teleological** description of processes that systems that self-organize must possess; or you could tell the story, or define Active Inference, from the point of view of neurobiology and **ethology**, from a point of view of, say, **predictive processing**, and describes what it entails.

And I've used the word "Bayesian mechanics" before, because from the point of view of the physics definition, it would be a teleological description of a Bayesian mechanics that necessarily arises, you know, (with certain assumptions) from any self-organizing system.

One *key* thing about Active Inference, which I think would be important to put in the definition in the ontology (I'm not sure if it's already there…): -- It's *beyond* predictive processing. It's beyond **sentience**. And it emphasizes, or *reflects*, the pragmatic turn at the beginning of this century (epitomized by the **4E**s - **embodied**, **embedded**, **extended**, and the like), to make it clear that sentience is *active*, and that you are talking about the circular causality of engagement of any **particle**, *person*, or **plant**, with whatever is out there.

So, that would be certainly one thing to emphasize in terms of what Active Inference means.

The "inference" is interesting, in the sense that it does imply a process, and a process with **purpose**, which is to **infer**; which is why I keep using the word, "a *teleological description*" -- of something that's actually underneath the hood from the point of view of physics.

Getting the *name* right

20:11 One final point here is: There's an easy confusion, I think, between, first of all, *active* inference and ***passive* inference**. So, that's certainly something which probably needs resolving, certainly in the philosophical literature. So, I often come across philosophers who say, "Well, there's *passive* inference, or *perceptual* inference (which is just basically inferring states of affairs in the world on the basis of some sensory evidence). And then there's the '*extra*' bit, which is the *active* bit which is: 'Now you're in charge of *gathering* that sensory evidence upon which you are now going to prosecute your perceptual inference.'"

That's an interesting dichotomy, which I'm not sure is a *correct* dichotomy. If it's not right (I'm not sure that it is *not* right, in the sense that it is a useful distinction) -- but certainly is *not* what Active Inference was originally *termed* to mean.

You know, by conjoining "active" and "inference," there were a number of motivations. First it was a generalization of **David MacKay**'s **active learning**, but probably more importantly, it was a nod to the notion of **active sensing**, and **active perception** -- that perception is in and of itself, an *active* process, a *constructive* process -- that you have to put policies, plans, and action into the game. So that, I think, would be one important aspect of Active Inference to define, and I don't know that it has been defined so far. So, you know, perhaps it's your job to define that.

Inference about the consequences of action - in the future!

22:06 The other thing which is important, I think, in terms of emphasizing what Active Inference entails actually comes from that **enactive** perspective, which is *inference about the consequences of action*.

And that has an important but really simple concomitant: that the consequences of action are in the *future*. And that means you now have to think: if you're thinking about Active Inference in terms of teleology or as a **normative theory** of behavior -- of **sentient behavior**. And you have to now think about -- I should qualify: When I say *normative*, I mean it can be operationally defined as an **optimization** process that, in turn, requires you to define the **objective function** or **functional**. And that's important practically, because if you're now thinking about sentient behavior, Active Inference, and its influence about things that haven't yet happened, because you haven't yet acted, then you're necessarily talking about objective functions or functionals that are about states of affairs in the future. And that is an important move, and something that Active Inference embraces, which goes beyond **predictive coding**. Much of the literature in the 1990s, and subsequent, much of the literature that inspired that sort of enactive perception or **active sensing** take -- **situated cognition** take on sentience originated in things like predictive coding. But predictive coding is *not* what is meant by Active Inference: you can do predictive coding just by , if you're a statistician, just minimizing **Variational Free Energy**. That's only half the game, once you move into the world of Active Inference.

From a teleological perspective, you have to do that, you have to form beliefs about **hidden states** of affairs in the world , using the perceptual side of perceptual inference - but that is only in the service of rolling out into the future, and deciding what the best thing is to do next. And that running out into the future and deciding clearly calls for an objective function.

So in Active Inference, that would be the **expected free energy**, which may or may not be unfortunately named - but that's what it is. And therefore, Active Inference sort of implies that you are committed to optimizing an expected free energy; and implicitly it's all about choosing the next thing to do.

So, for me those would be two *cardinal things* that should be embraced by a definition of Active Inference that, you know, transcend other normative approaches. So, for example, you know, **reinforcement learning** in behavioral psychology would be all about what the good things are to do, and you commit to a **loss function**, or a **value function** of states , if that was the kind of behavior that you're trying to describe.

If, on the other hand, you were all about the **psychophysics** of perception, or just building basal digital terrorist optimal recognition systems, where you weren't in charge of gathering those data, then your objective functions would be very, very different.

But what Active Inference says, well you can't carve up the two problem domains, because they're just both sides of the same coin. And thereby you're now facing the problem of defining an objective function that is fit for purpose, that does both the belief updating about **latent states** or hidden states generating the data, and *also* the best way to solicit or *cause* those data or outcomes *under* some prior preferences or some goal-directed constraints.

Is that a good long-winded answer?

26:45 *Friedman:*
Thank you for the comprehensive answer! It leads directly to our next questions, which are:

.edu Question: 'What is the Free Energy Principle?'

26:51 What is the *Free Energy Principle*? And especially,

.edu Question: 'What is the relationship between Active Inference and the Free Energy Principle?'

26:54 What is the *relationship* between Active Inference and the Free Energy Principle?

27:02 *Friston:*
Right! Well, that's, I think, a slightly easier question to answer!

The Free Energy Principle is just a **variational principle of least action**. Why is it special? -- or *not* formally identical to all the other **variational principle**s that we use?

If you look under the hood, right from quantum, through statistical and stochastic, to classical mechanics -- Well, the only thing that differentiates, really, the variational principle of least action that *is* the Free Energy Principle, is that you're paying careful attention to the separation of states to which you apply that principle - the separation of states into the states *of* an agent, or a particle, or a part of a person -- and the *outside* states.

So technically, , if you were in statistical thermodynamics, for example, you'd normally *assume* that separation, in terms of some idealized gas that was contained within the container or heat reservoir, or a heat bath -- without really worrying about where the heat bath or the heat reservoir *came from*.

But the Free Energy Principle says: Well no, you can't really do that. You've really got to attend very carefully to what *licenses* a separation of different *kinds* of states, so you can assign to the *inside* of something -- and the *outside* of something -- and the states that mediate the exchange between the inside and the outside. And then you get into the **Markov** blanket and Markov boundary literature.

So, just to summarize: A Free Energy Principle is just a **principle of least action**, by which I mean, that there is a description of dynamics in terms of the most likely paths any system will take. That is the special provenance of a **partitioning**, or a separation, of the states of some universe into the states that are owned by an agent (or a particle), and those that are not, and the states that mediate the exchange between them. So that would be the Free Energy Principle.

Active Inference, as I say, is a sort of teleological spin-off from the Free Energy Principle, in the same sense that you have now at hand a principle of least action. It allows you to identify, simulate, define the *most likely* paths, **trajectories**, or **narratives** that a system will pursue under certain conditions. And those conditions are just that there is an **attracting set** of states which that system will converge to, or will look as if it's *attracted* to.

So, sorry! – What I was working towards, was the notion of an attracting *set*, as a **metaphor** for equipping that physics with a teleology; and that teleology is nicely illustrated by the notion of *attraction*. So when mathematicians talk about **attractor**s -- in the particular case, in the Free Energy Principle, these are these sort of **pullback attractors** or the kind of attractors that you get in **random dynamical systems**.

There's a *proper* and *natural* tendency to think that these *particular* states of the attracting set *literally attract* in the sense of gravitational attraction, or any other kind of attraction: "They *pull* -- they *pull states towards* them." So that, to me, would be a teleological interpretation which, I think, is much closer to Active Inference. -- That you're saying, "That "*influence* is a process that has a *purpose*; and the underlying Free Energy Principle allows you to say the way it *looks*, as if self-organizing systems show these certain *properties*; they're *attracted* to certain *states*; they're attracted to certain *paths*; and we can describe those in terms of the teleological ontology." And that would be Active Inference.

One *practical* difference between Active Inference and the Free Energy Principle, is that the Free Energy Principle is *just* a principle. It's neither right or wrong; it's just like **Beren Millidge** has noted: it's sort of like **[Amalie Emmy] Noether's Theorem** or **[William Rowan] Hamilton**'s principle of least action. But as soon as you start to say, "Well, I think that this principle applies to *this* population or person or particle," that certainly commits you, or requires you, to define the attracting set of states - a pullback attractor (in another jargon, the equivalent would be a generative model); and as soon as you commit to a generative model to explain the teleology of *this* system, or *this* agent, or *this* person, then you've moved into [or "from"? -Ed.] the world of non-falsifiable principles into falsifiable hypotheses, because you could have chosen the *wrong* generative model, and thereby there will be evidence for choosing *this* generative model or *that* generative model.

So, the relationship between Active Inference and the Free Energy Principle is *operationally* quite simple: Active Inference is the application of the Free Energy Principle to a particular system. But in that application you're bringing a lot of teleology to the table, and more specifically you're having to commit to a particular generative model. And as soon as you do that, that becomes *your theory* or *your hypothesis* about what is an apt description *for this system*. So, a number of interesting distinctions, in terms of the relationship between Active Inference and Free Energy Principle that I imagine your ontology is already addressed, or it's certainly addressing.

33:43 *Friedman:*
Well, we'll get there! Thank you for that excellent answer!

For the next question: Lorena, please read it out.

.edu Question: 'How and Where Does the Idea of Information Play a Role in FEP / Active Inference?'

33:52 *Sganzerla:*
Still in the spirit of broad questions and broad terms, and that, I think, comes in line with (what) came before. So, how and where does the idea of information play a role in the Free Energy Principle, and how does it relate with Active Inference -- in the sense of,

what is something to keep in mind when thinking about information dynamics in Active Inference?

34:20 *Friston:*
Right! Well, these are great questions! I'm getting the hang of this now. You just want me to talk! I've presented a question to another talking! -- Which I'm very happy to do. Are you sure you want me to do that? Or should this be a conversation? Perhaps it'll turn into a conversation at some point. Anyway.

So, information. It plays a dual role, in the sense that information theoretic formulations underpin most of the derivations behind that principle of least action. And it can be no other way -- in the sense that all mechanics from physics, is really articulated in terms of probability densities or distributions.

And as soon as you have a mechanics, or a calculus, or probability distributions, you're effectively in the world of information theory. And you see that at many different levels. One nice example of this is that the central quantity that we often use to score the likelihood of being in a particular state -- if you're a statistician, that would be the **marginal likelihood**; if you were fluent with an FEP ontology, it would be **surprisal** (or more simply **surprise**)-- and that is just basically the **self-information**. If you're a physicist, you look at this as a potential -- it's a negative log probability.

So you *start*, really, when thinking about the physics, with this central concept of self-information, which, I repeat, can be read as a potential function, or a surprisal function, or surprise. And it is the thing that the Variational Free Energy is a bound approximation to. So at that level -- and then every other move you make mathematically, in terms of the expected self-information being the entropy -- and why that is important as a characterization of various probability distributions in the setting of self-organization -- would testify to the fact that information theory is absolutely central to all the maths that underlies the physics of the sentience that emerges from having a distinction between the states of the system and states that are not in the system, namely the **Markov blanket**.

Having said that, I think "*information*" to most people's minds usually means more. Certainly in the folk psychology context, it's really information *about* something. And the FEP Active Inference has, I think, something quite special to bring to the table here, that goes beyond information theoretic treatments that you get in communication and signal processing and rate distortion theorems. All of that kind of information is just your extensions of information theory that inherit from self-information or the implausibility of a particular event or message -- or, in more abstract domains, such as sentience and consciousness, you would go to something like **integrated information theory**. But that is all about this "**Shannon**-esque" kind of information.

The opposite, the other kind of information, which is information *about* something -- So, what I wanted to try and put on the table, is the very fact that you've got this Markov blanket, or separation of states on the inside and states on the outside, means that now you can equip the states on the inside with the role of encoding posterior conditional Bayesian beliefs about states on the outside. And that introduces, technically, a different kind of **information geometry**, a different kind of information theory -- where, *crucially* now, you can read the *internal dynamics* as containing or *having information about* what's going on, on the outside. And this is a really important move, equipping your neuronal dynamics or **variational message passing** or **belief propagation** in a computer, with an information geometry, that now allows you to read off the state of the computer, or the state of the neural activity, *in terms of* what it is encoding, or the information it contains *about* the outside.

And so that sort of *dual aspect information geometry* has been celebrated to a minor extent in the philosophy literature by **Wanja Wiese**, asking the question, "Is this really the maths of sentience?" -- where you now have information *about* things. And in a sense, that really is the heart of the Free Energy Principle -- or Active Inference, anyway -- in the sense that it equips that information geometry. I mean, technically, what you are saying is that any particular internal state of a computer, or a person, or a brain, now can be read as encoding a Bayesian or a posterior belief about other states, namely, hidden or latent causes outside the Markov blanket. And that defines, technically, something called a **statistical manifold**. And as soon as there is a statistical manifold, there's an information geometry. And any movement on that manifold necessarily implies *a change in your Bayesian beliefs*, namely **Bayesian belief updating**. Which means now there's an *interpretation of neuronal dynamics*, movements on a statistical manifold on the inside, in terms of belief updating. So the notion of Active Inference, as the process of belief updating, really , rests upon this fundamental notion that there's information about stuff that is encoded or parameterized, by the internal machinations, and the mechanics, and the dynamics of the inside.

If you're trying to educate people in terms of how they should understand information, I think it'd be important to differentiate between:

INFORMATION OF THE FIRST KIND

41:27 the mathematical notions of Shannon information, or self-information –

INFORMATION OF THE SECOND KIND

41:42 And the information implicit in an information geometry; namely, the information about something. This second kind of information is implicit in an information geometry and the sentience that is afforded by Active Inference -- when now you're understanding *neuronal* dynamics, or message passing in the computer on some Forney factor graph. Because in *this* instance, each of those messages, or those neuronal dynamics, can now be read as belief updating -- namely *changing your mind* about other things -- so that the stuff on the inside has information about stuff on the outside.

	Associated terms
"Information of the first kind" Information theory	Shannon information Self information Surprisal / Surprise Log evidence Log marginal likelihood Mutual information
"Information of the second kind" Information geometry	Bayesian beliefs Posterior beliefs Conditional beliefs Information length Information geometry

Table 1. Two kinds of information, based upon the transcript.

42:26 *Friedman:*
Thanks for this important answer.

And we're going to How can the integrity of the Active Inference **process theory** be maintained when blankets, blanket states, and generative models are being interpreted in novel ways? What do you think of discussions around Markov, or **Pearl**, Friston blankets, etc.?

43:12 *Friston:*
All right, that's an excellent question. I have quite a technical answer! So if it's getting *too* technical, tell me now -- [laughs] I'll try and get back to what you were really trying to unearth!

This is not a *fast moving* field; but [has] certainly been a delicate and important area of discussion over the past few years.

So, in the original introduction of Markov blankets, there was an explicit nod to Pearl's construction of Markov blankets, and how Markov blankets are used *practically* in terms of simplifying message passing in computer science. However, that may have been something of an oversimplification.

Because from the point of view of the Free Energy Principle, the kind of causality that the Free Energy Principle deals with is *not* the kind of causality that people, particularly people like Pearl, but also people dealing with things like **Granger Causality** deal with.

From the point of view of the Free Energy Principle: that starts with a stochastic differential equation, or a random dynamical system written as a random dynamical equation -- and OU [Ornstein-Uhlenbeck] processes being simple examples -- in physics these would be Langevin-like equations.

Common to *all* of these starting points is time, and evolution, and dynamics. Now, there is *nothing* in Pearl's formulations (well, certainly there's nothing in Pearl's book), on causality, that deals with time. And I know that, because -- before the days of PDFs and being able to go and search particular words -- I had to go through [laughs] and find out -- there's one paragraph that mentions dynamics! If you were in statistics, computer science, you know -- this will be the world of dynamic Bayesian nets. This is their "take" on something which is actually much more universal, which is basically the universe as a Markovian dynamical process.

So, just stepping back, the challenge now, is to articulate *independences* -- that underwrite Markov blankets in the sense of Pearl, in terms of dynamics. So you've now got to *link* two quite distinct fields, which is basically the fields of dynamics and Langevin processes, and things that have paths of least action -- to the world of statistics and Pearl-esque independences and causality cast as interventions that have observable consequences.

The problem in doing that linking, is that you have to really abandon the notion of causality in the world of Granger Causality and Pearl, because causality is baked into, and is inherent in, writing down any differential equation (be it stochastic or random or deterministic), in the sense that *states cause motion*.

So the causality in this context would be a more control- theoretic causality. So, that means that you *can't* then use the causality concept later on. But it does mean that you've now got to derive from a dynamical Markovian calculus the necessary conditions that would lead *to* the conditional independences that are necessary to define **Markov boundaries**.

Just to slip in here: The Markov blanket is composed of *minimal* blankets: namely boundaries, in the sense of Pearl. And on most recent analyses, it looks as if the blanket is actually *two Markov boundaries*, in the sense of Pearl.

But to get to the sense of Pearl, you've got to think very carefully about, "What are the constraints that lead to the conditional independences?" -- where those constraints are specified in terms of equations of motion and things like the amplitude of random fluctuations.

So, once you've seen that that is the link that needs to be made, that actually simplifies the thing! It simplifies things, in the sense there's no real latitude for interpretation. So, I'm going back to the part of your question: "Blankets and generative models are being interpreted in novel ways." And I don't think there's any latitude of... any novel interpretation other than the… ... Sorry! If "in novel ways" you mean "the best way," or "The correct way -- and we just haven't got that yet!" -- then I would concur entirely with that! [Laughs.]

If you think that there is some latitude, there's some library of insightful reinterpretations and redefinitions, all of which have equal veracity, then I would suggest that's *not* the case. There's only one way, and there's only one Markov blanket, or there's only one particular *partition* that can be articulated in terms of Markov blankets. And the only "novelness" there is really in tying down very precisely and defensibly how you get from a Langevin formulation to a Markov blanket.

At the moment, the "novel" way of doing that looks as if it's that the conditional independences arise from **sparse dynamical coupling**, or **causal coupling**. So, if you read the causality as the influence that a state has on the motion of itself or any other state, in this sort of minimal Langevin-like description of the universe, then it is the sparsity of influence, or the **sparsity of coupling**, that *leads to* conditional independences. And if the system has a sufficiently *rich sparsity* of conditional independences and implicitly coupling, then it will have a particular partition; and if it has that particular partition, then the Free Energy Principle holds.

So, I think the discussions around Markov, Pearl, Friston, and blankets are essential -- they're fascinating. And the conclusions of those discussions (that I think I'm gonna probably have to refer back to the underlying maths) - and that maths is all about connecting Langevin formulations of physics to the kind of calculus that Pearl has established, in a more statistical sense.

51:04 *Friedman:*
Thank you for the educational answer! This brings us almost to the end of the .edu section.

So, I will pass to the final question to be read by Dean, who had several excellent points and questions.

So, Dean, feel free to ask however you would like.

.edu Question: 'What Is the Difference Between “Subject Matter Expert” and “Prediction Matter Expert”?'

51:25 *Dean:*
Good morning!. The question is: what's the difference between a **subject matter expert** and a **prediction matter expert** -- and how does this relate to your mode of interaction?

51:40 *Friston*:
You're going to have to unpack what "subject" and "prediction matter experts" means, for me.

51:48 *Dean:*

For me, you become a "subject matter expert" by gaining a certain amount of concentration in a particular field or area. And you become a "prediction matter expert" when you are able to think more distributively, more dispersively. And so, when I read some of the things and listen to some of the stuff that I've heard you talk about – You brought these two worlds together.

And so, I'm interested in hearing what you think - in terms of introducing some of the ideas and principles that you brought into a world where, traditionally, we focused on concentrating -- whether it's materializing something from an engineering perspective, or deciding what's in and what's out. You've brought in another aspect to look at. And I'm curious what you think of that.

52:49 *Friston:*
Okay, that's a fascinating distinction! I'm not sure it's terribly important what *I* think about it, because clearly *you're* the expert on this.

But it certainly would be fascinating to consider the conditions under which you were able to *simulate* the emergence of a subject matter versus a prediction matter expert *in silico*, for example. This is a proof of principle that these are both effectively Bayes optimal ways of responding to a particular environment.

And my guess is that you would be able to do that relatively easily, by appealing to the ideas that you find in applying some of Active Inference notions to **structure learning** and development, where the basic idea is:

The 'Prediction Matter Expert' Worldview

53:43 IF you've got a very volatile environment, by which I mean that there's lots of uncertainty in the contingencies; or possibly there are lots of random fluctuations, that are irreducible (in terms of your ability to predict the outcome of the trajectory of latent states of the world in which you are becoming an expert) -- *THEN*, (formally: in terms of the **precision** of various likelihood mappings or probability transition matrices in discrete state-space generative models) -- *when* you parameterize your beliefs about that irreducible uncertainty and volatility, *then* agents that believe (or have inferred) that they are in a very volatile, changeable, capricious world usually become better at the prediction side of things, in the sense that they rely less upon deep past experience, and assign more precision or more potency to the more recent evidence.

So, they have a different style of evidence accumulation, and also, they have the right level of uncertainty about what will happen next. So, it looks as if in their predictive engagement and epistemic foraging in that world, it looks as if they are better at predicting changes -- because they're not committed to a particular explanation or understanding of how their world works.

The 'Subject Matter Expert' Worldview

55:43 On the other hand, if you create a world which is incredibly predictable and learnable, then, over time, the natural pressure to minimize free energy translates into a pressure to minimize *complexity*, namely a way of modeling your world and your exchange with it, in the simplest way possible, in accordance with Ockham's principle. And what that leads to is somebody - it sounds as if - it's somebody who becomes a subject matter expert. But the subject matter is their lived world, that has now become so predictable that they do not entertain all possible other outcomes, because they have precise beliefs about the way that things will unfold, and they can make very wise, very parsimonious -- or using parsimonious degrees of freedom, they can make moves and become very expert in the way that this particular non-volatile, predictable (i.e precise) world works.

Making Our Worlds More Predictable

56:56 And the link with aging here is that: If you allow for the fact that we create our own environments, and your many levels of Active Inference will permit -- or is a way of framing -- our eco-niche construction. The story people tend to tell is that: as you get older, you basically make your world more predictable and you become a subject matter expert in your own lived world. So, I like the example: I no longer go bungee jumping nor go to discos, because my world is very, very predictable. And I'm, you know, very much am expert -- because my world is basically my conservatory, my study and my bedroom. So, I'm a complete subject expert on that! (Laughs.) You take me out to a disco, and I will not be able to predict what's going to happen next. Because I'm old.

'Prediction Experts' in the Making

57:47 Whereas, adolescents, and children, and certainly newborn infants -- or newborn artifacts discovering their world, which is *full* of uncertainty -- they are not yet subject experts. And the epistemic pressures or motivation for them to learn about, "What happens if I do that?" and "What can I control? - What can't I control?" - that will make them very quickly into prediction experts, until they become sufficiently fluent that they can now engineer their world to make it non-volatile. And then they presumably will become subject matter experts.

Simulating Cognitive Styles

58:29 So, yeah. I'm sure that would be fairly simple to simulate, using all the toy Active Inference schemes that we currently use. And it would be really interesting, if these two different kinds of synthetic agents did develop some cognitive styles and confidence in what they were doing that looked exactly like the distinction you're talking about! I'm not sure it would work, but if it does that would be an illuminating proof of principle.

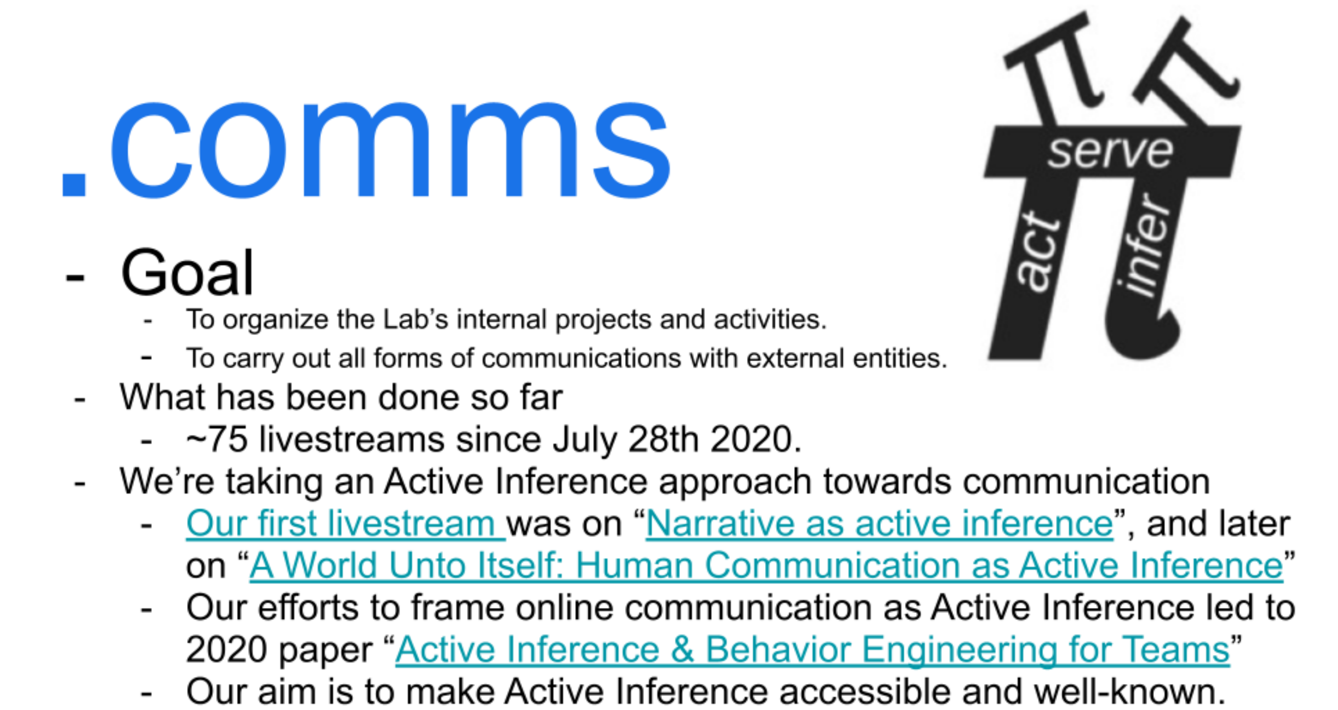
59:02 *Friedman:*
Thanks for this answer -- and for this session from the Lab and .edu.

Moderator's Recap: 'Maturing Cognitive Styles'

59:06 That last answer really spoke to the importance, also, of intergenerational learning.

At this point, we will take a break, and we will return for .comms.

Session 2 (.comms), Communications



00:01 Hello, welcome back! This is the second session of the ActInfLab symposium on June 21st 2021.

.comms Organization Unit Overview

00:10 We're here in the .comms, or communication, organizational unit. The goal of .comms is to organize the Lab's internal projects and activities, as well as to carry out all forms of communication with external entities. So it's like our connective tissue and our neuroectoderm, in a way.

What has been done so far, is that we've had about 75 Livestreams, variously on presentations and participatory discussions, since July 28th, 2020.

We're taking an Active Inference approach to communication, and learning by doing. Our very first Livestream was on the paper "Narrative as Active Inference," and shortly after "A World unto itself: Human Communication as Active Inference." That's something that we like thinking about here, and that we want to explore. Also, some of our Lab members framed online communication and team collaboration in terms of Active Inference in the 2020 paper "Active Inference & Behavior Engineering for

Teams." Our aim here is to make Active Inference accessible, well known, and well understood.

So let's get right to the questions, Karl.

.comms Question: 'How can we “show not tell” the idea of Active Inference? (E.g. through embodied experiences, experiments)'

01:30 The first question is, "How can we show -- not tell -- the idea of Active Inference, for example through embodied experience, experiments, or what other mechanisms?" How can we best communicate in a way that makes it resonate?

01:47 *Friston:*
Well... Pursuing that very interesting notion -- of using the principles of Active Inference to optimize the role of the .comms team. At its simplest, Active Inference means that the imperatives for all behavior (and it's likely that most behavior is of an epistemic sort) is to resolve uncertainty. So if you want to engage people and be a service to the people you want to engage -- which may be internal members of your own team -- and then you've got to know, what they *don't know*. Because, that will define the epistemic affordances that will get them *engaged with you,* and *you with them,* that will incur the best kind of belief updating.

Embodied Illustrations

02:53 So, practically, what that might mean, is that(, it may well be that... you um…--> one has to identify didactic or informative illustrations that are tailored, or specialized, to the person or people that you're talking about.

You know, I have never thought about using embodied experiences before! But that's a brilliant idea! You're just illustrating to people who want to know "How *my* body and *my* mind works?" -- to illustrate to them the mechanics of it working, using the language of Active Inference. And it can be very, very powerful!

Sensorimotor Attenuation

03:47 One example of this would be --

Using **saccadic suppression** as an illustration of the potency of getting your beliefs about the predictability of sensory evidence right.

If you're a physiologist,you would... you would know this as **sensory attenuation**.

If you were in **machine learning**, you're working with **transformers**, this would be, I think, **attentional selection**, basically deploying the **gain**, or switching on the right **channels**, in order to select those data that are going to resolve the most uncertainty or maximize the **information gain**, subsequent on this sort of covert action, often sold as a sort of "**mental action**" in the philosophy literature.

So that *mental action* is really endemic, and a vital part of our sensory engagement with the world -- and beautifully illustrated by saccadic suppression. This speaks to the notion of *attenuating* the sensory consequences of your own action; so that any evidence that you're not actually acting is precluded from your belief updating.

Parkinsonian Paralysis

05:14 A clinical example of this would be **Parkinson's disease**, for example: If I'm sitting still; and I wasn't able to ignore all the messages from my muscles that tell me, "at the moment I am sitting still;" then I am never going to be able to realize an *a priori* intention that I'm going to initiate a movement -- Because as soon as I initiate a movement, I have… I put in place a plausible hypothesis that I'm lifting, that I'm going to stand up. Immediately, all the evidence at hand suggests that I am not standing up, so I'm going to revise my belief: "No, I'm not standing up; I'm not in the process of standing up.", And it becomes impossible to move. So that would be an example of what would happen if you didn't have this capacity to attend to, or to select or apply the principles of optimal Bayesian design, in terms of selecting those data for your own belief updating.

More on Saccadic Suppression

06:15 But a really pragmatic and easy example of that is saccadic suppression, when we do the simplest of movements - epistemic foraging, which is moving our eyes, making saccadic eye movements. Because, when we do that, we actually induce *masses* of visual information on the photoreceptors in the retina, sometimes referred to as **retinal slips**. So when I look from the left to the right, there's a *flood* of information that *I have caused*. And yet it is not *useful* information, because it doesn't tell me anything I didn't already know. So what the brain does,... it suppresses that information by transiently suspending the precision -- or the **Kalman gain**, if you are taking a **Kalman filter**-like perspective on predictive coding as one kind of **variational filtering**).

And that's really easy to demonstrate to an audience. Just get them to either fixate on an essential stimulus, and then pay attention to something that's moving around. Or the converse: they fixate on the thing that's moving around, and then ask them questions about the central stimulus. And with the right timing it's a very potent illustration of, beyond just gathering information, but actively selecting and triaging that information in accord with the principles of your optimal Bayesian design.

Exemplary Experiments

07:46 So I haven't thought about going beyond that; but I'm sure there are lots of lovely examples of embodied experiences that really do illustrate Active Inference in action, as it were.

Ideomotor Theories; Hypnotism

08:04 I'm just reminded, because Active Inference could be read as if you like a 21st century version of **ideomotor theories**, which were very popular in the 19th century.

And, of course, that was demonstrated through embodied experiences in a very alluring way, through hypnotism and the like! So I can imagine somebody doing a sort of 21st century version of hypnotism and all those wonderful Victorian illusions about the way you use your sense organs or deploy them actively. But now in the service of just illustrating some basic phenomena that underwrite Active Inference.

Visual Illusions

08:52 In terms of experiments (or the classic ones that immediately come to mind) that are really engaging, are visual illusions.

On one reading, all visual illusions are just ways of getting out your perceptual priors in the context of Bayesian inference. If you can conjure a particular pattern of sensory information that *you* know was caused in one way, and yet you think your subject or your audience has sufficiently precise prior beliefs that it could only be caused in *another* way, which is not the way you caused it; and then you let them experience that; and then you reveal how you actually generated those data - then that's a very powerful way of demonstrating the innate priors, the sort of formal priors, in terms of the **connectome** or the the *sparse coupling* on a factor graph. And that, again, is part of the lived experience. So I think visual illusions would be -- and there are loads of beautiful illusions out there -- and all that one would have to do, is to harness their beauty and allure; and use them as a vehicle to give people insight into the their own, usually **sub-personal** priors about the way that the world is constructed.

Simulating Illusions

10:17 And then, in *my* world, what you generally try and do, is to actually put this *in silico* by just, you know, creating little *in silico* creatures. And *because* you've now got Active Inference with this information geometry, you now have the opportunity, not *just* to simulate what these creatures *do*, but what they *perceive*. Because now you've got the quantitative estimates of their posterior beliefs. So you can actually show a subject who's *just* experienced a visual illusion, that this is perfectly Bayes optimal. And, indeed, when you write down this variational message-passing scheme in this synthetic subject, this synthetic person *also* experiences *exactly* the same illusions; and this is Bayes optimal, for this kind of work.

So you can leverage Active Inference activities in that sense.

Focus on .edu's Educational Work

11:16 And deliberately referring back to the .edu discussions - What Active Inference brings to the table:

Because it's got *information* about stuff *out there,* in the numerics -- you can go a lot further, than you can if you were doing, say, deep learning or machine learning. Because you've *got* this information geometry at hand, the *state* of your variational autoencoder actually means something in relation to a belief about what generated those data.

You can create lovely little movies, you know, showing what this *simulation of you* was actually experiencing.

So, I'm interested: Are there any other ways that you've thought about in terms of showing people?

Moderator's Recap, 'Developing a Curriculum'

12:07 *Friedman:*
Thanks for the answer! It's like "look left, look right, now you're an Active Inference agent!" And, as far as potential avenues for embodiment:

Somatosensory Simulations

12:14 Some of the work with Ryan Smith and others, bringing people into the *somatosensory dimensions* and their own priors and expectations about their *body* and about *motion* could be very powerful, as well as auditory modalities. And, indeed Active Inference is a framework by which we can think about how our perceptions are related to our inference and our action. So, in various domains, I think they'll be excellent experiments.

.comms Question: 'How Can Active Inference Engage in Better Dialogue with Adjacent Areas? (E.g. Machine Learning, Systems Engineering, Psychiatry/Neuroscience, What Other Fields?)'

12:44 And it brings us to our next question. You actually addressed several areas in your answer. You addressed machine learning, as well as neuroscience, as well as just everyday lived experience.

How can Active Inference engage in better dialogue with adjacent areas? For example: Machine Learning, Systems Engineering, psychiatry, and neuroscience, as well as any other fields that you think are relevant, too?

Active Integration: An Integrative Framework

13:12 *Friston:*

The obvious answer here is in either academic or commercial collaboration, and what would license that.

The simplest answer is that the Free Energy Principle and its (if you like) teleological correlative, Active Inference, and is not there, and was never intended, to *replace* extant theories. It was there , to *endorse* them, and to reveal the interrelationships between them. So anything that's worked and survived into the 21st century has some veracity and a proven utility.

And therefore it's just a question of reformulating or changing the words, so that people can see immediately how their particular formulation relates to somebody else's formulation, where both formulations are special cases of the most generic and simplest explanation -- which would from my point of view would be the the Free Energy Principle, and Active Inference in the case of sentience.

Cross-Disciplinary Interviewing

14:26 So, I think -- As an an **integrative framework**, you're very well positioned to say:

"Look, can we understand the way that *you* think about this; and can we now articulate this, either using simulations or mathematical analysis?

"Can we understand what *you've* been doing -- *in this integrative framework?* And if we *can,* can we show how it relates to *another* discipline's formulation of this problem?"

And sometimes you can get synergistic or added value from doing that. There must be loads of examples! You've written "Machine learning, Systems Engineering, Psychiatry, Neuroscience…" here.

Dialog with Machine-Learning

15:06 So, *Machine Learning,* for example: "How would Active Inference help Machine Learning?" At the moment, there seems to be two answers floating around. We've already discussed a couple of these issues in depth.

Machine Learning commits to (usually) a normative approach to good behavior, that can be quantified by a loss or a value function. But we've just said, "Well, if we now want these machines to learn to *act,* then we have to go *beyond* **state-action value functions**, and consider the *belief- based calculus* that *is* Active Inference, which is all about the reduction of uncertainty."

So now you are in a position to say: "Well, look! If you consider your objective functions as a *part* of a more *generic* "objective function," think what you might be able to get from this!" And, of course, what you might get from this is a deep learning scheme, that actually can now go and solicit the right kind of data to optimize its own learning.

And, you know, people in **Bayesian RL** [Reinforcement Learning] might argue: "Well! That's what we're *doing*" - with a series of bright ideas and heuristics! - "to try and *augment* classical value functions!"

But you can say, "Well, okay - You've clearly put a lot of work into that! But there is actually a *simple* objective function already *out there,* that is provably appropriate to describe systems that self-organize and maintain themselves, that actually has what you want! Why don't you try *this?*" - for example. So that would be one example.

You have to tread carefully because, you know, a lot of people have dedicated their lives to solving these problems! And they're very reluctant to change their rhetoric, or see their contributions as a special case.

But in many instances -- certainly from my perspective, mathematically -- they *are* special cases. And sometimes, if you catch the entrepreneurs, the innovators, the creative academics, at the *right* stage in their career, *before* they have committed to a particular church, or ideology, or calculus, or group, or company -- and you can actually point them in the right direction -- they become extremely creative!

Dialog with Systems Engineering

17:43 And I'm not so sure about *Systems Engineering.* But, certainly, I always celebrate the expected free energy as with just taking away various bits and pieces, various sources of uncertainty, as reducing to **KL control**. And then what I say is, what KL [Kullback-Leibler] control is [is] what grown-up engineers use in a control-theoretic setting! That would be another example.

Dialog on Tolerating 'External Uncertainty'

18:14 You could also (I don't *know* this, because it's not my field) -- but certainly in terms of introducing, say, a **fault tolerance** in control theoretic approaches in engineering, where the fault tolerance required uncertainty about the operation of some *external part,* you could, again, motivate a more complete objective function, that takes you beyond KL control and introduces the information gain into the mix.

Because to get *from* the complete objective function *to* KL control - you have to ignore uncertainty about the latent states that are in the mapping *from* latent states of the plant you're controlling, *to* the sensors or the observables. So you're moving from a partially observed Markov decision process (for example), to an observable one; and then expected free energy becomes KL control - or risk-sensitive control, in economics.

So you could say, "Well, look, why don’t you just augment your KL control, and then put this extra term in? And now what you've got, is a kind of anticipatory fault tolerance, in the sense that if there's uncertainty about latent causes, that's *automatically resolved,* in the way that you go and switch on various sensors or switch off various sensors. As you know, there's a principled way of doing that!"

I think to have any influence, you need to be able to show or provide *proof of principle*, that this more integrative, more universal, normative approach to problems can offer speed ups, or increased efficiency, or do what the people actually in that field want it to do.

So (for example) you've got to be able to show that Active Inference can outperform "vanilla deep learning" by an order of magnitude. Which is easy to do, because of course most benchmarks in machine learning are actually inference problems! So if you just recast it, it's actually quite a trivial thing to do, just by saying: "Well, actually, what you've been dealing with is an inference problem!" -- which looks a lot like one-shot learning, from the point of view of somebody in machine learning.

But I think there will be some pressure to get people's attention, to make yourself attractive. They will, first of all, find you *interesting;* and also have the potential that they can place an **epistemic trust** in you. You've got to give them a *clue* and a *cue,* as to why they should engage with you. And very often there's a two-way, or two-road, exchange.

One simple example of that, which I see emerging in the field, is the use of deep learning to **amortize** certain mappings, when they can be amortized in Active Inference schemes to evaluate the expected free energy, for example, or doing very deep tree searches.

So that's the kind of innovation you've seen coming out of 20-year-olds at the moment, who haven't yet decided whether they're going to do deep learning or Active Inference - because they want to do both, and do it very, very effectively. So that's a nice example, from my perspective, on the sort of *integrative role* that could be played - or *you could* play.

Moderator's Recap, 'Active Inference Dialogues'

22:15 *Friedman:*
Thanks! I really heard this "Yes! - And!" maxim from communication and improvisation. It's like, "Yes, there's been a disciplinary way of approaching it. *And* we're going to be working together to come back to first principles, or to make it more efficient. So that's really powerful!

.comms Question: 'How Does Active Inference Help Us Rethink the Nature of (Online) Communication?'

22:32 How does Active Inference help us rethink the nature of *online* communication, where so much of our communication nowadays does occur?

22:44 *Friston:*
That's a big question, isn't it! , And, certainly in the context of social media, politics, fake news, and the like, you could take that question in lots of different directions, which I won't do because that's not my field of expertise. [Laughs.]

'What did you *Mean?*'

23:01 But just off the cuff, in terms of first principles --

"What is communication?" It's the ability for me to infer what you meant. It's the hermeneutics problem. If it's a hermeneutics problem, that's most efficiently resolved in terms of **dyadic or multi-system interactions** -- when we come back to first principles - which is the generative model, when we share the same narrative or same generative model.

'Who Is Talking To Who?'

23:31 , "How does Active Inference help us rethink the nature of online communication?" Just from a first-principles point of view, it would be the importance of establishing, "Who is talking to who?" -- and (if you want to optimize the efficiency of that exchange - *literally* from the point of view of this principle of least action) - the *speed* with which you can resolve uncertainty and minimize your uncertainty or surprisal.

'Are You Like Me?'

24:03 And then it's ensuring that like-minded communicators are actually communicating, because it's only *them* that will understand each other. So everybody has to speak the same language, they have to commit to a shared narrative, and a shared generative model. And then by things like rate distortion theorem, or rewriting that in terms of Active Inference, -- the joint free energy minimization between two interlocutors -- *that's* the most efficient sort of *shared* path of least action.

"How does that help engineer, or intervene on, things?" I'm not so sure. Certainly, just in reference to communications with people like Maxwell [Ramstead] and other colleagues, there is this interesting notion that, "If the real problem of communication is not really the messages that you send, but the *inferring whether* to send the messages to this person or not," that itself now becomes conditional upon inferring, "*That's* a member of my in-group!," or "That's a creature, or a person, like me!" And then the question is: "How does self-organization (say, in terms of social media exchange) - how is that underwritten by an inference about the kind of people who I am listening to, or who I am talking to? And what are the basic principles of that?"

And again, in accord with the minimization of complexity in our generative models -- It may be a useful hypothesis to say that "There's an inevitable **coarse graining** of the way that we conceive of the people that we generate information for (say, on social media), and reciprocally; and the kinds of people that I will be able to solicit by listening to this Twitter feed, or that Wikipedia page, or this news channel."

So understanding how people carve up -- the degree of similarity to them -- may be very useful in just getting an idea of the dynamics of message passing amongst communities that will be defined by, on average, how each member of that ensemble (or individual) coarse grains and has a generative model of the kinds of people in the communication grain.

'Why Always a 50-50 Split?'

26:33 And just to finish this -- which is something I've heard - and I found it really interesting notion (that, again, would be great, if one could simulate this and understand the maths behind it) -- is that:

The only evolutionarily stable (from the point of view of the Free Energy Principle) -- the only one that will be selected by a process of Bayesian model selection, the only partitioning into in-groups and out-groups is a 50/50 in-group/out-group -- in the sense that anything that departs from that sort of dynamically unstable (but evolutionarily stable) partition, means that the smaller group, the out-group -- the odd man out -- will necessarily ultimately be absorbed into the larger group. So the only stable partitioning is 50-50. Which makes a lot of sense, when you look at Trump versus Biden, when you look at Brexit versus not- Brexit -- wherever you look, all the important allegiances, in terms of our political, ideological, and possibly even theological communication, seems to be split right down the middle. And perhaps it can be no other way.

So it'd be very, very interesting to simulate that, and see if that is a truism that inherits from all of these marginal likelihood or free-energy minimizing processes, implemented at multiple hierarchical levels.

You know: Communication *is just* message passing. And message passing *is just* the way you articulate belief updating. And belief updating *just is* the process of inference; which *just is* the paths of least action according to the FEP.

Moderator's Recap: 'Rethinking Online Communication'

28:25 *Friedman:*

The 50-50 politics, it's maximally confusing! - something we all experience. And a few key points there about the nature of online communication, is that, at the core, it *is* dyadic, even when you're broadcasting to many. It's actually about that connection and the hermeneutic relationship of unpacking meaning.

And then also you brought up the importance of context, and identity, and who's talking to who, and our inferences about that - which is essential to rhetoric, and something that often gets left off when people take big-data approaches to online discourse.

.comms Question: 'How Does Active Inference Help Us Think about Science Communication and Participation?'

29:00 The next question is:

How does Active Inference help us think about science communication and participation? Specifically, as we move into broader citizen-science initiatives, and as scientists are in the loop - something you've been recently involved in as well, with society and with decision making. So:

As science and the nature of science is changing - Who is doing it, and how [do] they communicate it; how does Active Inference help us navigate that?

29:30 *Friston:*
Right! Well, I'm sure you've thought about this much more deeply than I have. It's just drawing upon my experience you know, in terms of science communication during the coronavirus epidemic.

Yeah - I think you're absolutely right. As with the previous questions, I think you can take the principles of Active Inference, and just think about, "What does that mean for optimal communication and belief updating, and shared belief updating, and shared narratives?" - or not - and use *that* as a point of reference for the way that you articulate your own science. And you've asked all the challenging and exactly-right questions, about how you communicate, how you engage other scientists, or other partners, within or beyond academia. And I think the same principles apply exactly to the public.

And just to reinforce your beautiful observation that "all communication is dyadic" from the point of view of the person communicating: So it's *this* kind of person (as a unitary object) I am talking to, or *this* population, or *this* mentality, on *this* discipline. So it is, I think, fundamentally dyadic, from the point of view, the person generating the messages, that may or may not incur belief updating in the recipients. And these kinds of principles, I'm sure, would be useful in terms of science communication.

So at that level I don't know that there's much that I would have to what you already know - and will, and possibly already are, implementing.

Active Inference as a framework for thinking about data collection

31:15 There is another level, though, which is using Active Inference not as a model for the way that we work and communicate and participate, but as more a statistical, or observation model of data.

So, in a sense, you can use the principles of Active Inference really to make the most of data pertinent to a particular domain. So again I'm thinking here of the dynamic causal modeling of the epidemiological and behavioral data that has been generated by the coronavirus epidemic.

You can certainly use the perceptual inference side of it, (if you like) the Bayesian filtering side of it; but also in principle the the data mining, or the optimal Bayesian design, to select which data are useful (or not), in a very practical way when assimilating big data in the service of understanding the system at hand.

Modeling the Epidemic

32:26 So, if the system at hand is, "How does a spike propagate from one neuron to another neuron in a neural network?" or "How does a virus propagate from one person to another person in a population network?" - then you can certainly use the data to apply Active Inference to build generative models of how you think that occurs.

And what *immediately* confronts you is, you've got to put in *all* of the things that generate those data. So you can't miss out any factors that are important, be they psychological, be they behavioral, be they viral, be they transport-related -- all of these things have to go into your generative model to best explain the data.

So, when we do this in a practical way, we use the instance rates from PCR testing, *and* Google mobility data, *and* Department of Transportation data - *anything* that speaks to them and reduces uncertainty about *all* the factors necessary. They're entailed by your generative model - in this instance, a discrete state space model.

And the Active Inference is not explicitly part of it, in the sense that we're not trying to predict people's behavior. But it does serve an indirect guide through the principles of Bayesian optimum design. And all that basically means is: "Do I invest computational resources, and thereby incur computational and statistical complexity, by including or attending to *this* kind of data, or not?" And then you can actually evaluate the information gain by including *that* data, or *that* data.

So, for example, "Do you need Google retail estimates and workplace activity, or just one?" If you include both, that means that the complexity increases; and literally you have to wait another half hour before you get the results for your dashboard! [Laughs.] Or - "Do you or do you not have a more parsimonious model?" -- in the same sense of that saccadic suppression of retinal slip. And you've actually said, "No, I don't need that -- I've got everything I need. I got the *right* kind of data, just by focusing on *these* data."

And then, once you've got that in mind, you can now go foraging for different kinds of data -- different collaborators from different disciplines, who've got different perspectives. But also, crucially, different data to try, that will inform and shrink your uncertainty about the model parameters -- and also, very importantly, about the structural form of the model: "Do I need this node?" -- "Is this interaction important or not?" -- "Is this degree of nonlinearity justified by the data?" So all of these questions affected your hypotheses about how this system is responding, or would respond if you intervene on it -- all of those questions now become amenable to an evidence-based analysis, because you've got a generative model underneath the hood.

So that would be a more practical application of the principles that underwrite Active Inference, even though your computer program is not actually *doing* Active Inference. But it's certainly been *deployed* using the principles of Active Inference

Moderator's Recap: 'Science Communication'

36:19 *Friedman:*

Awesome! And we heard that integrative approach: "*Yes,* we're going to include multiple data sets, potentially of unconventional type; *and* we're going to have a principled way of deciding how to include that data". And also as you brought up at the end, who to include in the conversation. And there was one piece you said in there about the *dyadic nature of communication,* where a speaker is always, (I think you said) "speaking to a person, or to a group, or to a community."

.comms Question: 'How Can We Appropriately Interact With Shared and Nested Generative Models Across Scales (Person, Team, Community)?'

36:47 And it relates to our next question which is: "How can we appropriately interact with shared and nested generative models, potentially across, scales -- be it person, team, or community? Do we think about these levels of analysis as Active Inference agents in their own right? Or how do we, for example, speak to a community or speak to a level of analysis that's broader than the personal?"

37:17 *Friston:*
Yeah! I think that's a great and challenging question! Clearly, there has been some provisional work in academia, looking at sort of "*Markov blankets of Markov blankets,* which is effectively, from a stats point of view, from a physics point of view at least, what we're talking about here.

As a physicist, you'll be tackling this with things like the apparatus of the renormalization group -- which tells you immediately something interesting: that the existence of this nested structure, if it is a renormalization group, means that there are certain functional forms that are conserved.

So what that means is, from your practical point of view, that there will be certain kinds of behavior that are actually conserved at different scales. So what works in terms of talking to your children should also work as a president talking to your community, or a governor talking to your state, or a team leader talking to your assembled team -- Simply because, in order for there to *be* a hierarchical nesting that supports that hierarchical structure, that has to be this conservation, usually mathematically written down as the functional form of the Lagrangian (or it could be the marginal likelihood, or the surprise that we're talking about) -- that underwrites these most likely paths, or paths of least action.

So that, paradoxically, makes the problem slightly simpler! Because, what you're saying is: What works at one level, will work at *all* levels - all you've got to do is find the coarse graining operator that takes you from one level to the next. So what that would look like, I think, would be very, very application-domain specific. So I think that there is a great challenge ahead, which is taking the single-particle FEP approach now into a world where it *matters,* where the world is actually an ensemble of particles.

Political Physics?

39:45 And we've already discussed the importance of thinking about worlds where all the particles are identical. Whereas, actually, half the particles vote for Trump and the other half vote for Biden! And this is interesting to reflect upon! Pre-21st century physics, that was so powerful in articulating this kind of dynamics, *because* it *just* dealt with the simplifying assumption that my idealized gas was an ensemble of identical particles. And then you can spin up from that equilibrium physics and everything that led from Carnot cycles and engines, through to current technology. So it's a powerful assumption, if you just make some simplifying assumptions. But we've already said, "Well, perhaps that's not the best kind of assumption to make, when you're dealing with *political* mechanics!" [Laughs.] You'd at least like one bi-partition in there!

And so that would require a revisiting of that kind of physics from our point of view or your point of view, basically simulating Active Inference agents, or ensembles of Active Inference agents, particles, but where now there's a heterogeneity in play; and then asking the questions: "Well, what are, at the *next* scale, the free-energy minimizing, or surprisal-minimizing, or potential-minimizing solutions at the next scale up?"

So we come back to our , "*Why* is it the case that people are all split 50-50?" -- Which has an enormous impact on the interactions at the scale below.

So I think, to tease… (I'm just hand waving here, because I don't think there are any any formal answers.)

And I think those formal answers will probably have to come out of agent-based, and possibly stochastic agent-based, modeling initiatives. But with the "twist:" You're making each agent itself an Active Inference agent. So while each individual member of the ensemble is trying to minimize their free energy; also the *ensemble,* through cooperation and the shared narrative, is minimizing the *joint* free energy. -- And what that means, when you move from one scale to the next scale.

If you're in physics, I imagine that this is the problem of "beyond non-equilibrium steady states;" because you're actually now dealing with the *multi-scale aspect* of non-equilibria. So at best we have good models of turbulent flow and solenoidal dynamics in laser physics, that take us beyond equilibrium physics where all the particles are the same, into non-equilibrium physics. But I don't know that there's an equivalent maths or metaphor, in physics that would really speak to the hierarchical nesting. So I think this is a really open and important research area, that I can only recommend is dealt with by numerical analyses basically predicated on underlying principles.

Moderator's Recap: 'Agreeing to disagree'

43:06 *Friedman:*

Thanks for the answer there! And it made me wonder if "agree to disagree" is a narrative that can be shared even when there is a 50-50 split.

.comms Question: 'How Can We Move People and Teams Into the Co-Transformative Space?'

43:15 And It brings us nicely to the final question of .comms, which is: "How can we move people and teams into a co-transformative space; or, as some of your recent work discussed, an *interactionist* space?"

43:34 *Friston:*

Well, I'm sure you know the answer to some of these. I'm now realizing you already know the answers, because your knowing smiles when I say something that you recognize!

So actually answering that on the basis of what you just said -- I think that's another really useful insight - that "agreeing to disagree" is a *surprise-minimizing, Bayes-optimal* explanation for the exchange with others. But it does rest upon committing to the hypothesis that "You are not like me; you are not like-minded; and that's okay." So I've now classified you as somebody who's not like-minded.

And I've resolved the ambiguity among the hypotheses that "You are either like-minded -- Or you're not like-minded." Normally, we resolve your first impressions within a few seconds, based upon all these epistemic cues we offer each other to define the sort of person that we are.

So we make that job as easy as possible for us, and signaling to make this "so we *know our place.*" And I use that phrase because, of course you know, there's a paper called "Knowing your Place," that exploited a shared generative model that allowed you to be in a particular position in some space, even if you and I share the same understanding of political ideology. But I know my place (because I'm right-wing) and you [know] your place (because you're left-wing), or vice versa -- and then we can quite happily exchange but agreeing to disagree.

So I think that that's a wonderful perspective to have, and to endorse it, and that is a Bayes-optional perspective from *both* sides of the disagreement. That's resolving uncertainty, and in a bounded rational way.

'Confirming' a 'Commitment'

45:31 So, applying that notion to co-transformative space –

It reminds me of the problem where certain patients in psychiatry have committed to a particular inference about whether they belong *out there,* in that kind of environment, or not; and they have decided that they *do not* belong out there, and that those people are not like them; and they start to avoid. (So in a very simple-minded way, if there are any psychiatrists…) in this example… -- But I think it's illustrative and useful in that respect.

So, take depression or agoraphobia, you know, which is a completely Bayes optimal response - *if* I have committed to the hypothesis that out there is full of people who are *not* like me; and potentially will upset, confuse, and render me uncertain; and possibly even injure me in some way. So *withdrawal* into your house, or into that silo (if you're working in teams), is a perfectly Bayes-optimal response that says that "You've got a precise belief that this is where you belong, these are the people that you speak to, and *not* those people!" And, that's usually perfectly functional. In psychiatry that would be a neurotic defense.

But it can become pathological when you become housebound; or say, if you've got a pathological hypothesis, like your body got dysmorphophobia, and you nearly die because of a failure to eat properly.

[subSection "It Can Be Another Way"]

47:14 So when you say "co-transformative," I imagine what you mean is, you want to transform two teams into one team, or at least enable them to work together. If that's right (and you're nodding partially, so I assume that it is), you're facing the same challenge that a psychiatrist faces in terms of enabling people to revise the precision of their precise beliefs about who they can interact with and who they should interact with.

That's not an easy thing, but it's certainly doable. And it usually reduces to presenting evidence to a group or a person, that *it can be another way;* so that they start to revise their prior beliefs, or at least the *precision* of their prior beliefs, in a safe space where it's okay to explore other hypotheses, enabling them to think about other ways of interacting. So this would normally be the objective of psychotherapy, basically by illustration -- very much in the same way you were talking about, illustrating or educating by embodied experience.

Very much, psychotherapy is thought to work like this. You provide a psychologically embodied experience where you can try out different styles and different hypotheses. And in so doing, you paradoxically introduce the *right kind of uncertainty,* about different styles of engagement and who you are and who you are talking to. And by relaxing that precision, you give the patient, or the naughty team that's become too siloed, the latitude to explore other ways of behaving. So I would imagine that most of the tried and trusted procedures to get teams into a co-transformative space, use one or more of those mechanisms.

What would Active Inference bring to the table? It would just bring the narrative that, "Everybody you're trying to get to talk to each other can come to share;" so they can *see,* through the process of becoming more collaborative, or exchanging ideas more fluently, or working with the same lexicon, or mechanics, or code. Having the same narrative will actually shape their prior space, and understand the mechanics of actually enlarging the hypothesis space in terms of interaction styles.

So, that was an incredibly hand-waving answer! But it was, in part, informed by my understanding of the question from the point of view of the psychiatrist who wants to transform the way that a patient relates to *her* world.

Drugs for Treatment…

50:47 Oh - and drugs can help. And I mean that literally! -- those drugs that are responsible, neurobiologically, for setting the precision. If you can temporarily suspend the precision in order to reveal other latent *a priori* hypotheses in terms of the way that I am, or the way that I interact, and the way that I behave, or the way that I perceive - that can actually have long-lasting effects, on bringing those other hypotheses to the table in the moment in subsequent interactions.

Drugs for the Terminal…

51:25 So perhaps the most compelling example of this, which is trending at the moment, is the use of **psilocybin**-assisted therapy, particularly in terminal care. If you know you're going to die of cancer in the next six months, there are certain hypotheses that are brought to bear in terms of how I would expect to feel, and how I engage with the world, and how I engage with my loved ones, as a *dying person* who is near death and the ultimate loss. Those are not necessarily the best or most functional hypotheses or ways of being!

There are other ways of dying gracefully, and gloriously. But to get at them, sometimes having a *managed challenge* to your **5HT-2a** receptors via things like psilocybin and other related drugs just allows you to suspend for a moment your very precise beliefs about "the kind of thing I am," and allows you to experience other ways of being and perceiving, which can be very useful when it comes to just trying out other hypotheses, in this is "your cancer journey."

... Drugs for Teams

52:34 … But, you know, one can also imagine similar scenarios, when you get locked in to a particular way of interacting either within a team or between teams, in a larger organization. So that would mean you have to go on a retreat, and take lots of magic mushrooms.

Moderator's Recap: 'Into Co-Transformative Space'

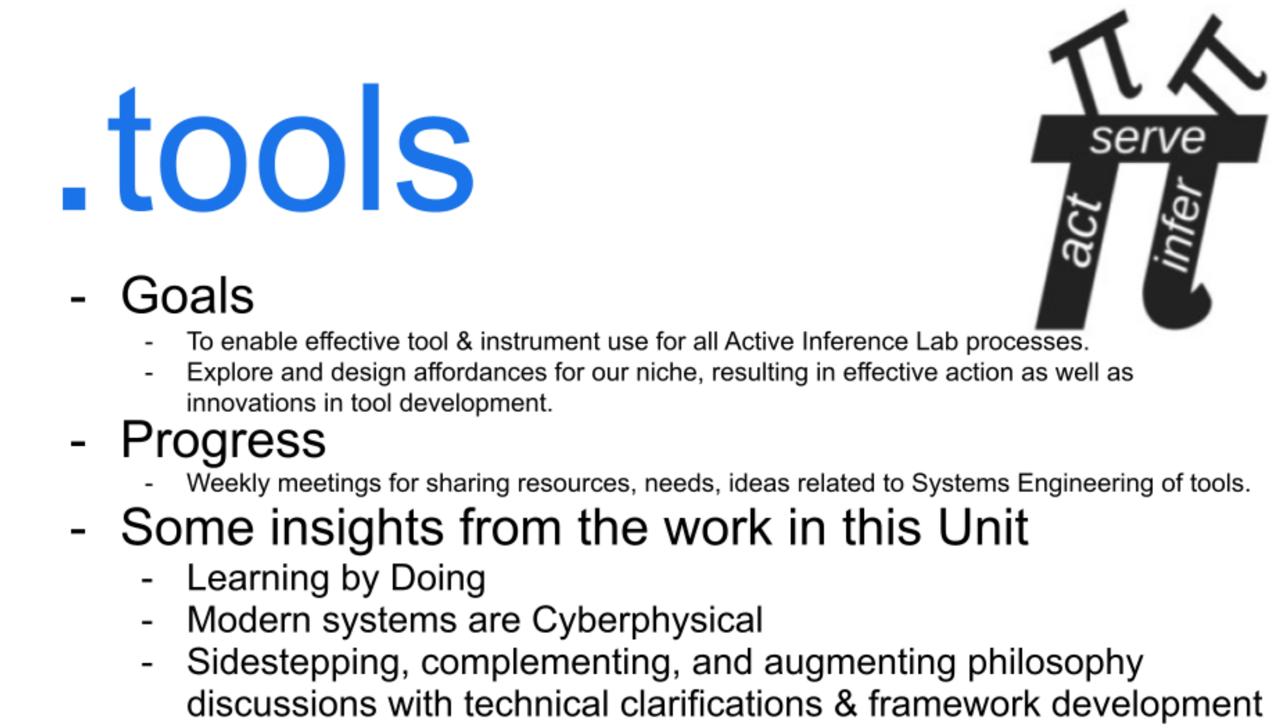
52:52 *Friedman:*
Never thought I would hear from you, Professor Friston, but there we have it: "Drugs for teams!"

Thank you for this excellent interval with .comms unit!

We're going to take another break, and we'll return for the final session - for .tools.

Session 3 (.tools)

.Tools Overview



00:01 Welcome back, everyone! This is our third session of the Applied Active Inference Symposium with Professor Karl Friston, hosted by the Active Inference Lab. It's June 21st 2021.

We're here representing the .tools organizational unit of the Lab - the third organizational unit in the Lab.

.Tools Goals

00:22 The goals of .tools is -- To enable effective tool and instrument use for all Active Inference Lab processes - so that's just using the digital tools affordances that we have better. -- As well as exploring and designing affordances for our niche, modifying our niche, resulting in effective action; as well as innovations in tool development.

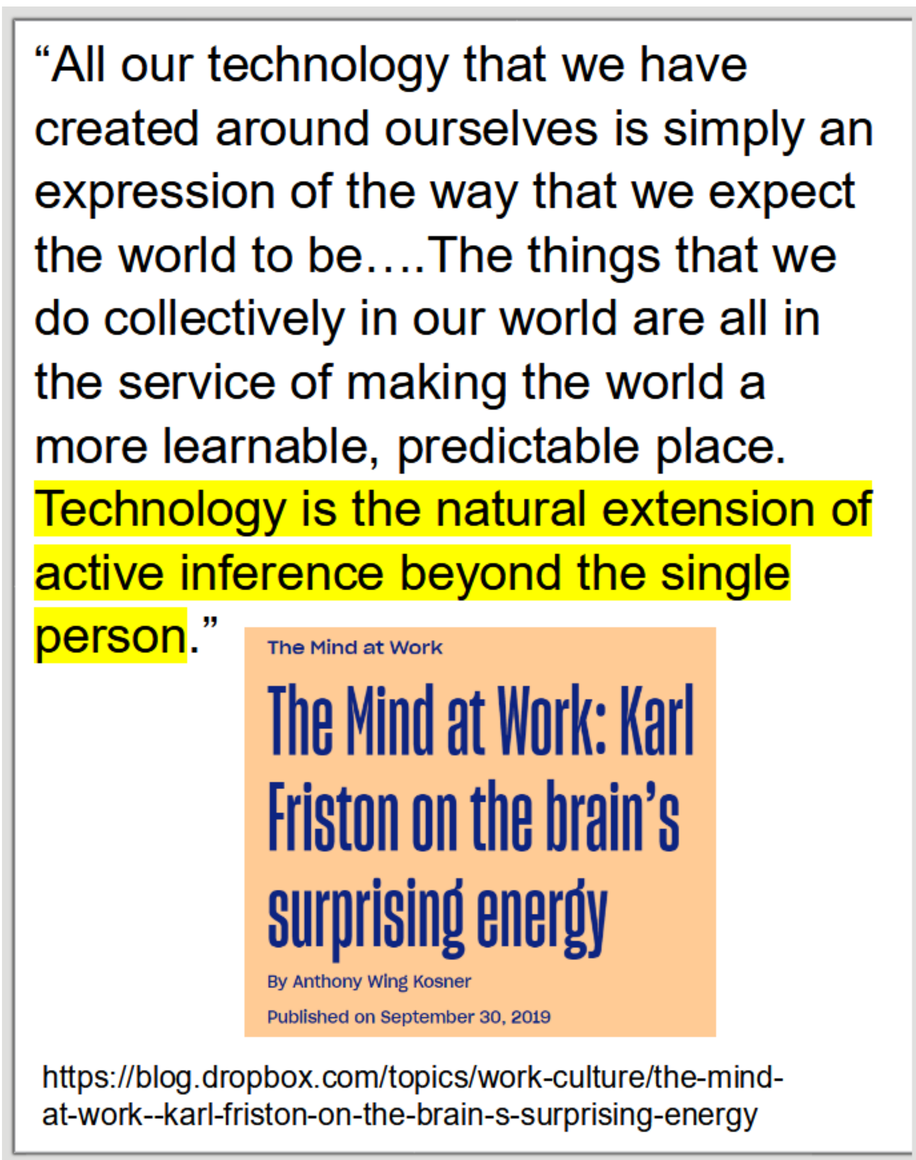
As with the other groups, we've been meeting weekly in Tools, and having a lot of awesome insights related to where Active Inference might come into play. And that's what we're excited to talk to you about.

Core Insights from .tools

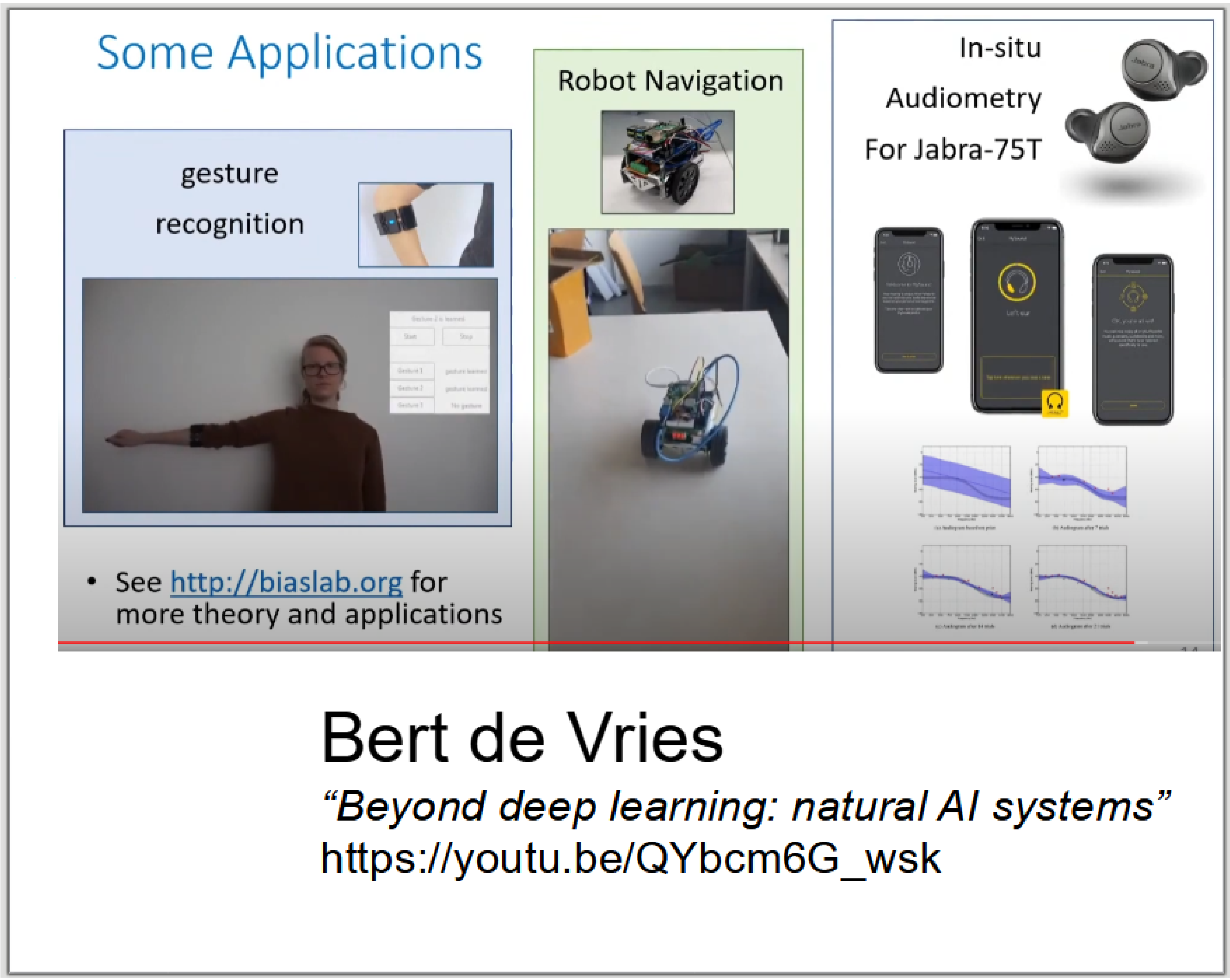
00:58 Some of the *core* insights from the work in this unit relates to learning by doing: The recognition that modern systems are **cyberphysical** -- everything is really intercalated with the digital. And also we found it really refreshing, kind of like a two-stroke engine, to be sidestepping, or complementing, or augmenting some of these philosophical discussions with technical clarifications.

And two ways in which we've seen that play out:

01:27 Here is a quote from *you* during a 2019 Dropbox blog post when you wrote that "**Technology** is the natural extension of Active Inference beyond the single person;"



which, of course, brings technology - far from being something artificial - into the realm of extended and embedded *cognition* in our niche.



01:49 And then, a slide from a very recent talk by **Bert de Vries** on "Beyond Deep Learning: Natural AI Systems," speaking to several applications in hardware and software of Active Inference - for example gesture recognition, robotic navigation, and also audiometry for hearing aids.

02:12 And one effort that we're starting up *now* is a **NetHack challenge**. It's kind of a video game played in text characters. And we're assembling a team with already multiple interested *participants* to get an Active Inference agent on the playing field so to speak, and have people maybe update their generative model when they see that it doesn't have to be a three billion parameter neural network trained for six months on the GPU -- but what if it's enough to just be curious and to want to succeed? Those are the kinds of things that motivate us in .tools.

.tools Question: 'How Can We Use Active Inference to Structure the process of innovation & tool development?'

02:50 We can off with asking: "How can we use Active Inference to structure the process of innovation and tool development?" And, "How can Active Inference concepts help us design for complex agents that are interacting in complex niches?" For example, thinking about niche modification, extension of affordances, reduction of uncertainty, or structuring of communications.

03:21 *Friston:*

So: The use of Active Inference to structure the process of innovation and tool development --

03:34 That is, , in itself, an entertaining notion -- in the sense that, *you are* a realization of Active Inference! And, you know, I'm mindful that the emphasis on *curiosity* as the imperative that drives most of our behavior is *exactly* the imperative that, as a scientist, drives me and most of the people I know - and in a sense, I would imagine, also drives your initiative and your laboratory.

So, all the questions you are asking are really, [Laughs.] "How do I make the next move, in order to resolve uncertainty about your particular *model* of how, say, **Artificial Intelligence** (A. I.) or human communication is going to evolve?" So, in that light, I think there are two levels to the answer.

The first one is just to celebrate and acknowledge that you are engaging in the scientific process as formulated by Active Inference; that you are on a journey of trying to satisfy curiosity that will be never ending. And that speaks to one of your themes in the previous slide about "learning is doing." The only way you're going to resolve or sate that curiosity is to go out there and see what happens. And that is exactly the right thing to do.

A more *practical-level* answer, though, speaks to the *tool development.* Because one of the fundaments of Active Inference is the appreciation that,

"*If* you just want to maximize the likelihood that *your* kind of world model or generative model (that *entails* the way that you exchange with and interrogate and ping a world), is the *right* world (that is articulated out there, in the sense of extended cognition for example, in terms of the software tools, or the educational tools that you're making available) -- *Then all* of this is still subject to the imperative to minimize complexity.

So, in maximizing the likelihood that these tools will be out there -- and in a sense you're saying, "This model, this way of narrating the way that the world works -- you provide an *accurate* description that is as *simple* as possible."

So, you cannot escape the complexity - I'm speaking like **Jürgen Schmidhuber** now – which is a *good* thing (in this instance)! That means you've got to find the simplest tools.

It's interesting that you highlighted **Bert de Vries**'s contribution. Because, again, just *practically* thinking, "what's the game" here? The game here is to find the best hypothesis, the best explanation for *my lived world* -- and my "*me*" could be Active Inference Lab's -- and the "lived world" is everything that you have to engage with, in terms of educational, commercial, or academic partners. So, you've got to explore the model space, to find the right generative model of the way that your system or your organization works.

Find the Right Generative Model!

07:35 The first steps in writing down the generative model are basically to define its structure in terms of the sort of hidden factors or latent factors and their interactions, and all that good stuff.

But it has to be done in the simplest way possible. So, what's the simplest way of writing down a, generative model? Well, it's to write down a Bayesian graphical model. What does that mean for the actual *coding*, practically, and the software schemes and implementation that you would either offer to people or pre-package in terms of user interfaces? Then it's going to be message passing on those graphs.

'Pack the Simplest Tool-Kit!'

08:18 I'm trying to get back to **Bert de Vries**'s **ForneyLab** formation. To my mind, that's the simplest, most generic bit of computer science that you would come across, in the service of finding the right software tools -- to build absolutely everything! -- Because:

Absolutely everything can be written down as a generative model! If there's a generative model there, there's a Bayesian dependency graph. If there's a Bayesian dependency graph, you know there's a factor graph. If there's a factor graph, then you know there's a message-passing scheme. What is that message-passing scheme? It's just a Variational Free Energy-minimizing message-passing scheme.

So I would imagine that, as tool development increases, there will be a move towards a common language that will look very much like Bert's Forney-style message passing. And within that, which is a good thing! -- Because that, again, speaks to this minimization of complexity -- and just course-graining the world, and your world at its coarsest level that will sustain an accurate account, or a precise account of what you want to achieve.

the tools just have to come in two flavors. They have to deal with continuous state-space generative models, to interface with the kind you need for robotics.

But the other flavor will be in discrete latent state-space models, that you need to do for, say, computational linguistics, or modeling the climate in various states.

And we know all the message-passing schemes that would be entailed by a commitment to one of those two kinds of models, in the sense of generalized Bayesian filtering for the continuous state-space. And by generalized, you include generalized coordinates of motion, which generalize things like **Kalman filtering**.

And on the discrete state-space side, you're talking about either **belief propagation** or variational message passing.

So, when you just think about it: What you have to do in providing tools of a software kind, or a simulation kind -- happily there aren't many choices you have to worry about. [Chuckles.] So, in that sense, all you need to do is to make sure that your tools accommodate both generalized Bayesian filtering, and belief propagation and/or variational message passing, and then you're using **off-the-shelf technology**.

Which brings us *back to,* "Well, what's the real problem, then?" Well, the real problem is writing down the generative model!

How would you unpack *those* problems, in terms of innovation and tool development? Well, it's solving the model selection problem. When describing the space of problems that are faced, say, with Generalized A.I. (or A.G.I., [**Artificial General Intelligence**]) you can unpack them at different spatial-temporal scales into the inference problem -- into the **learning problem** -- and into the **selection problem** -- by which I mean using Bayesian model selection to get the right structure. You know: "Do I use six, or twelve, layers in my deep neural network?" "Do I use a convolutional model; or do you use a transformer?" These are basically problems that are *solved,* if you have a mechanics that can score the structure, enabling you to select the right form. So *that,* I think, is going to be a focus of innovation -- yeah,--> it already is! But certainly in the near future, in terms of development, and in the sense that the inference and learning problems - they're solved problems; that you can just go to Bert and get your favorite message-passing scheme, or you can keep at the level of your educational or academic message-passing user **MATLAB** schemes that we generate here in London for toy problems.

And what is *not,* I think, a solved problem, and will require an innovative solution, is the structure learning problem, or the selection problem -- Exploring not "the right hypothesis," but -- we're (in the principled way) exploring *the space of generative models* you might want to bring to the table. And *that* has many, many different issues.

And, things that come to mind are, of course, that you could do it in a bottom-up way by trying out new hypotheses. Where do you get those from? You get them from experts in the field, because effectively they are bootstrapping themselves on the basis of our prior beliefs, or of your knowledge about how something works.

You can do it in a top-down approach by having over-parameterized… *over-expressive* models - but with very weak, imprecise parameterizations; and then use Bayesian model reduction to solve the selection problem. These are ways that people are thinking at the moment. But this thinking is innovative, because I don't think there are any clear answers.

So how would you use Active Inference to solve the structure learning problem? Well, in a sense it's already being used in the sense of Bayesian model selection as "natural selection;" but you really want to speed that up and make it work within your commercial or academic lifetimes! But I would imagine that exactly the same principles would be brought to bear there.

.tools Question: 'How can Active Inference Concepts Help Us Design for Complex Agents Interacting in Complex Niches?'

14:22 That almost answers the next one, "How can Active Inference concepts help us design for complex agents interacting in complex niches?" You just have to *build* these things as a proof of principle and hypothesis testing!

And the nice thing is, you *know* all the machinery and the tools that would be requisite in building these things, right from the variational message passing (using, say, ForneyLab) through to now!

You've got the right **fitness function** when it comes to using, say, a genetic algorithm to explore a structure space. And what is that fitness function? It's the evidence lower bound or the Variational Free Energy.

So, you've got all the maths in place. This is a question of simulating these things and providing proof of principle.

How you would translate that into the real world? I don't know at this stage, I'm afraid! [Laughs.] A challenging first step would be to actually use robotics, or *in silico*, or sort of hardware, or possibly (a lot of excitement at the moment) using **soft robotics**. And actually, you design your niche and see what happens.

And then turn your attention to niche construction -- where you now acknowledge that the niche itself is also succumbing to the principles - not of Active Inference in and of itself (in the sense that niches don't plan) - but certainly in the FEP sort of **vanilla free energy minimizing** approach.

So, yeah. I haven't actually thought about that before. But that's an interesting asymmetry, when it comes to simulating multi-agent interactions in the context of niche construction -- where *often* it is the case that the niche is *just* the other agents in an ensemble.

But *if* you now actually include the environment as part of the niche - that is playing host to all the denizens that are the ensemble of Active Inference agents -- *then* there is this distinction *between* the ability to plan the consequences of action, that would entail optimization of the expected free energy - *versus* simply reflexively minimizing surprisal, by minimizing free energy as an evidence bound.

And put that even more simply, more intuitively: You're either with generative models that support planning, or not. So there's nothing fundamentally different between these approaches.

If you've got a generative model that is a model of the paths into the future *consequent upon* how you act upon the world - that's a much *richer, deeper* generative model than the kinds of generative models that would be applicable for a thermostat or an environment.

And it's likely that the environment that I have in mind here - which is a warehouse, that you've got a sentient **robot** going around trying to collect the right things. So the robot can plan. But the environment, the niche, can't [plan]. It will still conform to the Variational Free Energy Principle. There will still be particles and things that are conserved. And they will still fall, and behave in a predictable way. There may even be a thermostat controlling the temperature - but none of these things are planning.

So, there's an interesting asymmetry that gets into the game when you're talking about complex agents interacting in complex niches. Part of that complexity has to be a specification of whether the complexity entails planning or not. And it just creates different problem spaces , certainly in the context of multi-agent simulations.

"carve up" the problem spaces, in terms of, implicitly, problem spaces that will only be explored by *doing.* And by "doing" I just mean actually realizing physically these processes, *in* the kind of situations that you think are going to be useful for the future.

Moderator's recap: 'When to Select?'

18:51 *Friedman:*

Thanks for the answer! It's really fascinating about using simulation, so that selection can happen within the generation of, for example a startup, rather than *between* generations. Because, of course, we can let organisms (or startups) proliferate, and then let pruning occur at the generational scale. *Or* there could be ways to design so that selection occurs within a generation, more like learning and development rather than intergenerational selection.

.tools Question: 'What Areas of Applied Active Inference are Exciting, Promising, or Important?'

19:21 This could be a broad question; but we're curious: What areas of applied Active Inference you think just might be exciting, promising, or important?

Active Inference for Computational Psychiatry

19:34 *Friston:*

My personal usual response to this comes in two flavors. The first is from the point of view of a **theoretical biologist** and a **psychiatrist**. If you can understand how a normal sentient artifact or person behaves, then that creates a space in which you can think about **false inference** and **false learning** - or certainly suboptimal, from the point of view of minimizing surprisal or free energy. That's a fancy way of saying understanding the **computational basis** of **psychopathology**. There's a whole literature on using Active Inference as a *normative* framework within which to provide an ontology of false inference , or failures, or aberrant Active Inference.

And why would you want to do that? Well, if it can all be reduced just to the good belief updating, and the good message passing, we actually have quite a comprehensive understanding of neuronal message passing, and all its physiology, and all the roles of various neurotransmitters, and microcircuits and neuroanatomy that underwrite that kind of neuronal message passing. And implicitly we also then have a fairly fine-grained understanding of the role of neurotransmitters and the consequences of pharmacological interventions *in* the context of experience-dependent learning and an inference of the kind we've been talking about. So from a translational perspective, literally translating the formalism on offer from Active Inference into the clinical domain - that would be *one* motivation for developing this theoretical framework.

Active Inference for Artificial General Intelligence

21:42 The other one is more in the line of technology and artificial general intelligence (A.G.I.). So then the question is: "Well, I now want to build sentient artifacts -- and not only *build them,* but build "brothers and sisters," so they are complex, and interact, and learn to love each other, in a complex environment that could include *me!*" And then, you've got a clear offer from Active Inference as to the design principles you might want to *use* to actually *build* these artifacts.

And then, there are interesting questions about, "What kind of artifact do you want to build?" And we've already discussed the difference between a thermostat, and a sentient robot going around collecting your next home delivery. There are different kinds of generative models. So now you ask the question, "Okay -- what are the exciting and promising kinds of artifacts, as defined by their generative models, that one *might* expect to see in the future?" And then we get into the world of generative models that support planning, so we're talking about deep generative models where they have a temporal depth.

Deploying Precision -- Mental Action

23:04 What are the next stages that you might be looking at? Well there's also a sort of **hierarchical depth** that would, at some point, first of all include the capacity to **deploy precision**. And why is that important? Well, as soon as you have *deploying the precision* as a process of inference, you have now a *normative theory* for this kind of *mental action,* or covert action.

One example of this would be -- (I don't know the technology; but I can be assured that I know what it's trying to do.) –

But thinking about transformer networks, and the way that attentional selection operates in this context: What you're saying is, you can actually optimize the attention selection as an inference process, using Active Inference or an evidence lower bound. And where you're now predicting what things to attend to, and what particular weights to switch on, and which weights to switch off -- at that point you can understand that as mental action. So when the transformers or variational autoencoders start to *now* optimize their estimates of the posterior precision at lower layers in an auto encoder, it's now acquired the capacity for mental action. And it now will pay attention to various representations, and possibly even various data sources.

That's not magical! We do that every day in the sort of MDP (Markov Decision Process) and use it to explain a lot of the attentional mechanisms implemented in the brain. If you can migrate that technology into deep learning, you would have taken one baby step towards true sentience, which is mental action.

Meta-Inference

25:02 The next step would be: "Okay, so, how can I now minimize the complexity of my generative model, where my generative model now actually includes this 'meta-inference?'" - in the sense, "I am now providing predictions about my inference, because I'm controlling the precision of hierarchically subordinate message passing." And at that point you start to think, "Well, perhaps one way of simplifying the computational complexity part of the inference, would be to carve up different states of attentional deployment!" -- in exactly the same way we're talking about carving up people into *Biden versus Trump* voters.

A simple, stable, complexity-minimizing carving up - which suddenly suggests to you that you can now equip an artifact with *states of mind.* So that they can be in four states of mind – they can be happy, they can be sad, they can be confident, they can be unsure. And they will have to infer, given all the evidence at hand, *including* the message passing lower in the hierarchy, what state of mind it is in.

And if you now include in terms of the sensory evidence - you know, the voltage on their batteries, or some measurement of their interoception - you now have something that's going very, very close to, say, Ryan [Smith]'s notion of emotions. So, now you've got - a part of the generative model is now inferring, "What state of mind am I in?" as the best explanation for all these interoceptive, embodied sensations. Not just the **proprioceptive state** of my actuators, but also "Are they getting a bit sticky?" -- "Is there some wear and tear?" -- "Are my batteries charged?" All of these things come together as part evidence in conjunction with all the usual visual, radar, acoustic inputs, to actually supply evidence for a **posterior belief** "I'm in this state of mind", "I'm anxious", "my battery's running out."

This *immediately* creates different **prior preferences**, cost functions if you like, that would be applied to your policies, because you've got a deep, changing model that plans into the future. So now you've got an artifact that not only has the capacity for mental action; it's now got the capacity to be in different emotional states.

The next step is to say, "Hang on! So there are these different states - Can I now equip it with a minimal **selfhood**?" "Can the hypothesis that 'I am actually an artifact,' provide empirical priors that reduce the complexity of my message passing at subordinate levels -- that is inferring the state of mind that I'm in -- that in turn optimizes the posteriors of the precisions of various likelihood mappings or preferences over policies?"

Self-Awareness

28:16 So, at this point, you're starting to get to artifacts that could have minimal **self-awareness**! The next stage would be, "That's only going to be ever useful, when you consider *dyadic interactions* again." Because the only rationale for having self-awareness, is to disambiguate *"self"* from *"other."* Which means that there must be some *confusion,* or some uncertainty, at hand - in order to justify the resolution of uncertainty, justify that complexity of the model! Which means that you have to be interacting with, or exchanging with, things that are sufficiently like you, to license the inclusion in your generative model, of a self versus other, or that "You are like me!" or "Not like me!"

So we actually come back full circle to what we're talking about before, in terms of inferring *"Who* am I talking to?" So, I think, this is structurally something quite fundamental about this inference problem: "Are you a creature like me, or not?" -- or "Are you like one of those?" -- "Are you a pet?" -- "Are you a plant?"

Just being able to carve up this world in a way that is **self-referential**, necessarily entails a minimal selfhood in the inferences of these, that speaks to the importance of getting the necessary evidence from the environment, that would license that degree of complexity. And the only kinds of environments that can license that degree of complexity, are when that environment, that eco-niche, actually comprises other agents like me - that make it, if you like, worthwhile me inferring, "Oh! It's me, not you, doing that!"

So I would imagine, *then,* the most promising applications of active influence in constructing sentient artifacts, pets and carers or people, things that you can converse with, would be to grow them -- certainly with themselves, but more importantly with *you* there, so they can learn by their doing with you there, so they're curious about you, and you're curious about them. And at that point, one could argue that's the only scenario which you're going to have any empathetic interaction, with these artifacts.

I'm sure there are other applications in terms of climate change, or commerce, or whatever. But in terms of imagining what you could produce, what you could sell, I would imagine that a **mindful** robot that actually is curious, genuinely curious about you -- because that will teach you something about itself.

Moderator's Recap, 'Exciting Areas?'

31:19 *Friedman:*
Thanks for that answer! The idea of tools for attention, and of design and engineering for "regimes of attention" (to use an Active Inference term), is really essential.

And what you were talking about there with the phone: First off, before the Internet, when there weren't other devices of similar kind, there was no need to *communicate out.* And what we've seen, is that - as there's more and more devices of similar or interoperable kinds, new levels of organization have to emerge.

Technological Self?

31:47 And then - I thought about the anxiety that a person might feel when their phone is running low on battery. Right now, that sensor reading is getting emotionally offloaded to the human. So we could have that anxiety on-device -- so let's have a more relaxing relationship with our phone! And then, as you pointed out, it would be the *incipient steps of selfhood,* or perhaps what they could even call a *self-phone* (if I'm allowed one pun per symposium).

.tools Question: 'What Kinds of Tools Have Been Most Helpful in Your Work & Research?'

32:18 The next question is: "What kinds of tools have been most helpful in your work in research?" -- which includes many areas such as SPM and DCM, that a lot of people who are just learning about Active Inference might not be very familiar with. And, what kinds of tools don't exist yet but might be helpful for Active Inference work?

Mathematical Tools for Active Inference

32:40 *Friston:*
So, the mathematical tools -- you know, I'm often asked this question of students, "Do I need to be able to do maths to contribute to this field? - and if so, what kind of maths?" I won't tell you what my answer is, but what I have found useful is certainly mathematics,

but not necessarily very high end; this is always Wikipedia-level mathematics; and in particular, dynamical systems theory, information theory, and linear algebra are probably all you need, to do everything, really. And indeed, you could read most of quantum electrodynamics as basically linear algebra, with a bit of probability theory underneath it! So that has been the mainstay. If there is one tool, that would be the tool and the language , of maths - and relatively simple maths.

'Teaching is Learning!'

33:36 The second thing is, the "Learning is Doing!" -- you know, "See one - Do one - Teach one!" ethos applies, very pragmatically, in this context. Which means, it's very useful if you can get students to actually *build* their own little simulated artifacts; and even more useful when they can actually code it out themselves. Which means you need access to a high level, at least third generation, programming language that a student can get fluent with should they want to. Not only to use the existing tools, but try and write it down themselves without having to spend years training as a computer scientist!

MATLAB

34:24 I found MATLAB *very* useful in that respect, not because it's terribly efficient (although I have to say, some of the matrix operators and under-the-hood tensor operators are much more efficient than people give them credit for, because it actually came from X-ray crystallography). However, what's really useful about it, is it uses the same *syntax* that you would find in a book on linear algebra, which didactically or educationally is really quite important when it comes to writing and reading the code. So we have deliberately stuck with MATLAB not because it's computationally efficient, *or* that it's open source (it should be - I don't think it is) -- but simply because it's configured in a way that people reading standard texts, "101" texts and linear algebra and the like, would be able to see how it transcribes into a computer language. So that's been a really useful tool.

High-Level Tools for Generative Models

35:21 And looking ahead, I imagine that one's gonna need open access and possibly more. I'm just thinking about, first of all, people like Bert and ForneyLab, in terms of very generic, very high-end specifications of message passing in computer science. It may be that that's the level you want people to actually compose their generative models and their artifacts. And they don't even need to know about linear algebra, and even less information theory. What they need to know is the language of the object relations, and how to specify just different classes of exponential probability distributions, and (you know) "Is it categorical; is it continuous; is it always positive, or can it be positive and negative?" And that may be quite sufficient to write down a factor graph, or a generative model. And then everything else is just off the shelf, and "it'll write itself."

So that would certainly be possibly helpful in the future.

.tools Question: 'What Kind of Tools Don't Exist Yet, but Might be Useful for Active Inference Work?

36:27 I'm moving on to "What kinds of tools don't exist at the moment." So I'm thinking of -- (I never used it, but I imagine would be) Bert's ForneyLab facilities, but offered as an application or a user interface, that allowed you to: Compose a generative model; Compose a generative process (the "actual world" that's going to be modeled); and then just click "RUN" and see what happens! That would be really useful, I think.

Amortizing Parts of the Inference Process

37:01 Having said that, the other side to "future-scaping" here, is (I repeat) this sort of *leveraging* more specialized or other fields; and, you know: Amortizing certain parts of inference; or Learning to infer; or (indeed) Inferring to learn; or Learning to plan; or Learning to *infer how* you plan…

Which Parts of the Inference Process can be Amortized? - Cerebellum…

37:29 -- or, Starting to see, "What parts of the inference process are *so conserved,* that they could actually be amortized and learned?" And certainly that looks as how that's what the brain has done! For example: there are people who think that the **cerebellum** has basically "*learned*" how the motor cortex does its online KL control or Kalman filtering, and therefore lends a fluency and a computational efficiency to the message passing -- which, in its absence - it doesn't mean you can't *do* something; it just means you can't do it as fluently, and as gracefully, and as quickly as you could *with* a cerebellum. Indeed, when you have a cerebellar lesion *all* that really happens is you become a bit clumsy and slow.

So, those kinds of tools - a quick and cheerful integration, or importing various amortization and deep learning technology into a Forney-style message-passing scheme that could support any kind of generative model, would be really, really useful.

38:51 *Friedman:*
Awesome, thank you!

.tools Question: 'What Kinds of Tools and Platforms Could Inform Trans-Disciplinary, Highly Contextual, Team Engaged, Participatory, Action Oriented Approaches?'

38:53 Approaching this nexus from another angle: What kinds of tools and platforms could inform transdisciplinary, highly contextual, and engaged teams that are working with these approaches? ActInfLab we hope to be working with others to be developing the Active Inference curriculum, and Body of Knowledge more broadly. But when teams are actually *using* these kinds of approaches, what kinds of platforms might exist to enable their work?

39:28 *Friston:*
Yeah, okay -- I have a strong suspicion that you know the answer to this! [Laughs.] So I'm trying to guess at the answer!

We've already talked, implicitly in the way that you presented the ambitions, and implicitly sent the questions, and all the answers are there. Whether that's trying to engage through education, whether it's trying to engage through insight, using (say) embodied experience, illustrations of the basic principles; whether it's supplying games or graphical user interfaces to facilitate the designing and enacting and the playing with generative models and Active Inference. -- I think these are *all* your obvious and laudable ways of leveraging what Active Inference has to offer .

Tools for participatory approaches?

40:44 *Participatory.* Yeah. The "Learning is Doing" thing, and the "See one! Teach one! Do one!" keeps coming back to mind. And the course completely licenses the participatory aspect. But what kind of participation did you have in mind? Are you talking about hackathons? Are you talking about playing games with Active Inference? Computers that start to hate you, or love you, or -- what level of participation were you…?

41:18 *Friedman:*
Yeah… Stephen, do you want to give a quick thought on a few kinds of participation -- or what does that mean to you?

Psychodrama

41:24 *Sillett:*
One area is quite interesting. In **psychodrama**, they use action methods like action sociometry, or spatial activities, to look at how people relate to their experience in a

dynamic way, so physically. So I've been looking at ways that spatial participatory approaches can *unpack* people's relationships to different niches, or different workplaces, or different types of embodied experience. And then that could be visible, to be put into Active Inference-type geometries.

42:08 *Friston:*
I see. Well, there's a great example!

Architecture; Epistemic Affordances

42:12 Two things that I've come across before, are architectural design and the importance of -- not just pragmatic affordance that says, "Can I walk up?" -- "Can I sit there?" But also the epistemic affordances: "If I look over there, what would I learn about the space around me, if I go around *that* corner?" There is embryonic interest, in *my* world, from the architectural sciences and architecture in and of itself, that could in principle be motivated -- (It's an odd discipline, because it's half like art and half like science.) But certainly some of their ideas are very much aligned with certain Gibsonian notions of affordance, and also the affordances, the *dual- aspect affordances* brought by expected free energy under Active Inference. So it's not just particular chair?" -- but also, "What will I learn if I so do?" And so things become epistemically attractive to engage with.

The Synchronization Manifold

43:32 The other domain is in entertainment and in music; and in particular the joy of synchronization and mutual predictability or minimizing free energy through mutual prediction, when singing or dancing together; or indeed interacting (with a slightly greater asymmetry) in terms of being a member of an audience, watching a band for example. one of the key things that comes out of *that* kind of research is ways of *measuring* the implicit generalized synchrony that you get from having this information geometry that I was talking about before, that rests upon there being a **synchronization manifold** between the inside and the outside. But if the outside is another inside from another person's point of view, what you now have is something called a synchronization manifold. So there's a mathematical image or space, to actually talk about mutual inference and mutual active inference and engagement and communication - singing together for example, or diachronically exchanging messages, that does actually translate mathematically into movement and belief updating on a synchronization manifold.

Measuring Generalized Synchrony

44:55 And that has real-world correlates. You can measure that using kinematic measurements. You're putting LEDs on people who are dancing together for example, or measuring heart rate variability or galvanic skin responses, or , doing eye tracking, or indeed EEG. There's quite a lot of work , in things like **hyperscanning**, and in ethology, and dance disciplines, in the arts, in the life sciences - where they do use a lot of these techniques to quantify the degree of generalized synchrony. What it would be nice to *do,* is actually try and *model* that synchrony, or understand that synchrony, in terms of movement on the synchronization manifold, which is sort of the mutual belief updating.

Circular Causality

45:53 And one thing which comes out of that, just in discussion if no further, is the *reciprocal [causality]*, the *circular causality*, that is necessary to maintain that generalized synchrony.

The particular synchronization manifold we're talking about, from the point of view of Active Inference, of course, is mediated across the Markov blanket, as are the active and sensory states.

But in general, you need to have *reciprocal* coupling in order to get synchronization. So **directed coupling** doesn't work. And if that's true, what that means is that engaging as an audience, for example, or participating as a spectator, will only really work in terms of establishing that generalized synchrony that you are chasing, and while you're chasing it well as soon as you have a generalized synchrony, you've got predictability for free for all. And that's a good thing, because that minimizes free energy. You know: the more predictable you can make the world, the better it is, from the point of view of free energy. But you can only do that if, as a member of the audience, or a witness to something, you can actually actively intervene on it.

So that brings to mind -- (I'm discussing this with friends of Maxwell [Ramstead]) -- If you wanted to promote virtual concerts online, for example, during the pandemic -- What you *don't* have online -- which is what glues things together, things like mosh pits in carnivals and festivals -- is you don't have the *audience participation* - the applause, the roars, the lighter waving, or the light waving.

So how would you get that back into a virtual experience? Because that would be *absolutely essential,* to actually engage people! Otherwise, you'll be just looking at a pop concert on television. So:

From Revealed Audiences --

48:08 *More than just revealing* the underlying correlates of that generalized synchrony in terms of the EEG traces of the dancers, or doing some sensory mapping from their motion to auditory input, just making the sensory evidence that supports the mutual inference more precise and more available - just by having it displayed, say, by putting motion in sound or sound in motion, or EEG, electroencephalographic, measures of performance, or the audience, visualizing that (and that *has* been done by people like **Paul Verschure** in Barcelona) --

-- To Empowered Audiences

48:54 -- *more than that*: To actually enable the *audience* to *change* what the performers are doing - - *or* perhaps what other members of the audience are doing -- you have to *empower* them to *close* that circular causality, to get that dynamical-coupling play, so you get the right kind of generalized synchrony.

you know that--> That sort of dynamical-systems perspective on synchronization and free energy minimization certainly speaks to a particular kind of participation and engagement, that does indeed rest upon action-oriented approaches. But crucially, it's the action of the *audience* on the performers, not the performers' action on the audience, that is usually what you need to pay more attention. Was that the kind of thing you were thinking about?

49:52 *Sillett:*
Yeah! - that's really a useful answer! We were thinking about that, and some participatory immersive theater type events, and other participation in collective meaning making. So that's the type of thing that we're looking at.

Community Power'

50:07 *Friedman:*
And it reminds me of *the Livestream affordance,* which is relatively novel, but allows people to be asking questions. And it enables not just efficient production of material in a one-shot approach, but it allows the feedback. And I can't help but add, that it's that affordance for participation, for example "speak now or forever hold your peace", that

expands the wedding into the community, because there is the opportunity for feedback. It's not just a breakaway clique - it's actually something that remains integrated through the affordance for participation.

.tools Question: 'How Might Future Modeling Involve Large Scale Patterns in Social Data Sets, and Working Back to Infer Hidden Causes? (E.g. Pandemic Modeling, Governance)'

50:40 (So) I'll turn to the last question for this section: "How might future modeling involve large-scale patterns in social data sets, and working backwards to infer their hidden causes, for example in the case of pandemic modeling, governance, economic, other situations?"

51:03 *Friston:*

Well, this is a very practical and very prescient question, because of course a lot of people are asking themselves that now, specifically with respect to pandemic models; but also the people who are exercised and have the interventional clout when it comes to COVID, are generally also the people who are invested in climate change problems as well. So there's a lot of noise out there at the moment about how we can harness the data assimilation and modeling advances made during COVID-19 and keep the momentum up to tackle climate change - and not just climate, but the economic structures, and financial structures, and informational structures, that are deeply interwoven in terms of climate change.

My answer is going to be somewhat deflationary. I've had this kind of conversation before, again with Maxwell [Ramstead] and John Clippinger and Kim Jones and related friends; and I'm due to have another conversation with him on Open World or (I can't remember), in the near future.

There's a temptation to take all the "high church" of the Free Energy Principle and Active Inference, and epistemic foraging, and all of that good stuff we were just talking about, and say "Oh, well, now let's make it work in terms of understanding (say) the pandemic!" And you *don't* need to do that. All you need to do is to apply the *good, scientific* principles that things like Active Inference appeal to, to the problem at hand. And it all comes back to the generative model.

So, all you're saying here is, "How might future modeling involve large-scale patterns of social data to infer the hidden causes?" -- is *just* a statement of, "We need the right generative models to make proper sense of the big data at hand!" And in saying "the right generative models," we need the equipment both to *invert* those models (in the sense of inferring the parameters' interactions), using the simple tools we've just talked about. They will just be lifting it from the laboratory, or continuing to use MATLAB.

The Structure Learning Problem

53:37 But the bigger problem is what we talked about, which is the selection of the structure learning problem. This goes beyond just "How many layers do I have in my deep network?" Much more important, I think, it's a factorization - it's knowing, "How many conditionally independent factors do I need to minimize the complexity - to get the *right* granularity - the right way of carving up the latent causes behind all the data that is available to me?"

So I think the pandemic modeling is a beautiful example of this, because: The factors that determine whether I infect you can certainly be written down in terms of virology and the ACE receptors, ACE-2 receptors, and base reproduction numbers, and transmission strengths, and transmission risks, and the spike proteins - but that's only half the story.

The Social Sides of Disease Modeling

54:42 The other half of the story is, "How likely are you to be at work, or at home, when I'm at work? Are you likely to be wearing a face mask? Are we going to be one or two meters apart?" So all these behavioral aspects start to become really important factors. And even beyond that: When it comes to making sense of the model, the likelihood part of the model that actually generates the data, can become *extremely* difficult to optimize when you start to think about, "What kind of data is at hand?" For example, just notification rates of new cases per day of coronavirus. Now you *might* think, "Oh, that's really great data." It's *really* difficult data to handle, because the different kinds of tests not only have differential false positive and false negative rates; but the different ways in which they are deployed, really compounds that in terms of the selection bias. So: "Are you testing people who are symptomatic? - What's the probability of being affected if you're symptomatic?" - Are you *not?* - Are you doing survey testing? - Are you doing the same amount of testing this week as you were doing last week?" *All* of these - what would be from an epidemiological or a behavioral science perspective really *un-interesting* factors, suddenly now become the most *important* factors in making sense of those data! But you only *know* that when you start to do the model comparison, the structure learning; when you actually commit to writing down the co-generative models

And that's certainly what I've learned over the past year, now coming up for a year and a half.

The Future of Modeling

56:19 The future of modeling -- First of all, it's obvious what the future is: It's just basically writing down the right kind of dynamical state-space models that account for data. But the future is really dealing with the problems of structure learning and model selection for any data, but in particular from the big data at hand in terms of pandemics or trafficking on the web, or climate change. So it's a really exciting opportunity!

Why do people want to do it? Well, once you've got the most evidenced (i.e the minimum free energy) model at hand, and you've got posteriors over all the model parameters and all the right interactions, then you can do all sorts of stuff in terms of reducing people's uncertainty about the future. Because you've quantified the uncertainty, and explained to them things that were once uncertain about and what *isn't* uncertain about. That has enormous implications for mental health and well-being; and possibly even feeding back into finance, because you always hear, "Well, the biggest determinant in terms of the markets is the market confidence. It's all about the uncertainty!" So if you can do uncertainty *quantification* in a principled way, using using this kind of modeling, you've done a big thing already.

'Interventions?'"

57:56 But then you come to monitoring putative interventions! You've now got a direct handle: posterior estimate on the latent states you actually want to make decisions on. So it's not the notification rates or the number of new cases in California today, it's a number of new people that have become infected today. And that's a *very* difficult thing to infer given all of these complicated aspects of the generative model. And then, of course, once you've established the *validity* of this model, in terms of its construct and predictability, *then* you can intervene on it. Then you can say, "Well, what would happen if I changed this? Or what would happen if I changed that?" And, "What would happen now? - What would happen in the future?"

Meteorology Beyond the Weather

58:42 So that, you know, you're suddenly in a world of quantitative modeling, where you can start to ask some very powerful questions, and *also* share with everybody who matters, the products of your inference. So you can now start to think about supplementing the weather forecast with an epidemic forecast, you know, "The virus in your area: And tomorrow we expect…!" You know, you can also do that for the markets. And these kinds of things, I think, are going to be more important when people, or when the current generation (*your* generation, I guess!) start to wrestle more with climate change, because they're going to want to - not just know whether it's going to rain tomorrow; they're going to want to know, at the level - not just the weather, but, "The climate - what are the indicators?" Because those indicators really contextualize, and inform *their* generative models about their place in the world, and that global scale. But to provide that kind of weather forecasting, that *meteorology beyond the weather,* you're going to need to have these state-space models properly optimized, and in a first-principle way in relation to their marginal likelihood on their evidence bounds.

[subSection "Future Modeling for Governance"]

60:12 And "governance." Governance is just policy decision-making based upon counterfactual outcomes. So that is *always* underwritten by these Bayesian beliefs. But you can't *get* the Bayesian beliefs, unless you've got a generative model. And that has the consequences of action in the future. There would be also interventions, either politically, or financially, or or otherwise.

Final words from Active Inference Lab

60:38 *Friedman:*

Thank you so much again for joining this Symposium! It was really a special moment for the Lab, and we look forward to continued interaction.

Thanks for everyone who's watching, and we hope that you participate in ActInfLab.

Supplemental Lists:

1. Subjects

2. References

3. Mentioned Names & People

4. Other Resources

1. Subjects

4E Embedded, Extended, Embodied, Enactive
5HT-2a receptors
a priori hypothesis
action-value functions
attract
attracting set
Active Inference
Active Inference framework
Active Inference Lab
active learning
active perception
active sensing
agent
ambiguity
amortize
attentional selection
Bayesian belief updating
Bayes optimal
Bayesian mechanics
Bayesian Reinforcement Learning
belief-based schemes
bounded rationality
causal coupling
circular causal
co-transformative space
death
deep learning
coarse graining
continuous state-space
directed coupling
discrete state-space
dyadic
dyadic interaction
dysmorphophobia
enactive perception

epistemic foraging
epistemic trust
ethology
Expected Free Energy
false inference
false learning
factor graph
fault tolerance
ForneyLab
Free Energy Principle
gain
generative model
hierarchical depth
hierarchical nesting
hermeneutics
hyperscanning
ideomotor
in silico
infer
information gain
information geometry
integrative framework
interdisciplinarity
Kullback-Leibler (KL) Control
language
least action
lexicon
loss function
machine learning
marginal likelihood
Markov blanket
Markov decision process
mental action
metaphor
mindful
neural network
neuroectoderm

soft robotics
somatosensory dimension
sparse (dynamical) coupling
state-action value function
state-space
statistical manifold
sub-personal prior
surprisal
surprise
synchronization manifold
synergy
teleology
trajectory
transformer
vanilla free energy minimization
variational autoencoder
Variational Free Energy
variational message passing
variational principle
variational principle of least action
visual illusion

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