**The Literalist Fallacy & the Free Energy Principle: Model-building, Scientific Realism and Instrumentalism**

**Abstract**: Disagreement about how best to think of the relation between theories and the realities they represent has a longstanding and venerable history. We take up this debate in relation to *active inference models* based on the *free energy principle* (FEP) - a contemporary framework in computational neuroscience, theoretical biology and the philosophy of cognitive science. Active inference under the FEP is a very ambitious form of model-based science, being applied to explain everything from neurobiological structure and function to the biology of self-organisation. In this context, some find apparent discrepancies between the map (active inference models based on the FEP) and the territory (target systems) a compelling reason to defend instrumentalism about such models. We take this to be misguided. We identify an important fallacy made by those defending instrumentalism about active inference models. We call it the *literalist fallacy*: this is the fallacy of accepting or affirming instrumentalism based on the claim that the properties of active inference models based on the FEP do not literally map onto real-world, target systems. We conclude that a version of scientific realism about active inference models under the FEP is a live and tenable option.

**Keywords**: Free energy principle; Active inference; Scientific realism; Instrumentalism; Model building; Idealisation; Approximation

# **1. Introduction**

Different kinds of problems beset scientific and philosophical inquiry. One concerns scientific realism. Scientific realism is the view that one reasonable goal of our currently best scientific theories and models is to offer literally true (or probably true, or approximately true) descriptions and explanations of what reality is like. Conversely, instrumentalism (or, scientific antirealism) is the view that scientific theories or models are nothing but instruments for the prediction and systematisation of target systems. Scientific models, on the latter view, *do* have explanatory power, and therein lies their utility. Yet, they are *not* truth-producing in the sense of representing parts of real-world, target systems (or, they do not have the aim of being truth-producing in the long-run).

In this paper, we take up this debate in relation to active inference models based on the free energy principle (in short, FEP-models). The FEP is a mathematical framework in computational neuroscience, theoretical biology and the philosophy of cognitive science. We shall ask: what is the relationship between the scientific models constructed using the FEP and the realities these models purport to represent? Our focus will be specifically on FEP-models and what, if anything, they tell us about the systems they are used to model. We call this issue *the map problem*: how does the map (theory, model) relate to the territory (real-world, target system) of which it is a map?

The FEP is a mathematical framework that postulates the characteristics any organism must have for it to exist (Constant 2021; Friston 2013; Kirchhoff et al. 2018). FEP-models state that any self-organising system that tends towards maintaining a non-equilibrium steady-state with its environment must minimise surprise. Surprise is an information theoretic term that quantifies the improbability of some outcome - e.g., a sensory observation given what a system expects to observe and what it actually observes (Corcoran et al. 2021). Active inference under the FEP states that systems behave as if they are minimising surprise by optimising two functions: a variational free energy function - measuring the fit between a model of sensations and actual sensations - and an expected free energy function - scoring possible action policies by which to remain in or reach preferred states of being (Da Costa et al. 2021; Friston 2013; Kirchhoff et al. 2018; Ramstead et al. 2018). The FEP, generally speaking, has been proposed as the basis for a grand unifying theory for the biological and cognitive sciences identifying mathematical principles that can be applied to model a variety of biological systems at all scales of organisation from cells and multicellular organisms to cognitive processes such as perception, planning, action and memory.[[1]](#footnote-1)

FEP-models have received a lot of attention both in the sciences as well as in philosophy. The last two years have seen a spike in papers defending instrumentalism about FEP-models. Instrumentalists about FEP-models rely on the following kind of argument:

1. Scientific models introduce distortions into the representations of target systems via idealisation and approximation;
2. Scientific realism requires that models provide descriptions of target phenomena that are literally true.
3. Scientific models are not true and accurate representations of their targets.
4. *Therefore*, scientific realism about models is false.

We shall show that this kind of argument is problematic. We argue that inferring instrumentalism about FEP-models on the basis of this kind of argument rests on a fallacy. We call it the *literalist fallacy*: this is the fallacy of accepting or affirming instrumentalism based on the claim that the properties of FEP-models do not literally map onto real-world, target systems. We shall argue that a version of scientific realism about FEP-models is a live and tenable option. In doing so, we follow Weisberg (2006, 2007) in taking scientific realism to be consistent with positing approximate, idealised and fictional models at any given time, yet where it is the long-term ambition to improve understanding of target systems by pruning away approximations and idealisation to the extent this is possible. On this view, scientific realism is not - or, at least not necessarily - the claim that models must be literally true: they can be probably true, partially true, approximately true or probably, approximately true (Stanford 2003).

van Es & Hipolito (2020) state that “it remains disputed whether its [the FEPs] statistical models are scientific tools to describe non-equilibrium steady-state systems (which we call the instrumentalist reading) or are literally implemented and utilized by those systems (the realist reading).” (2020, p. 1) They conclude that since FEP models are not true and accurate descriptions of their target systems, instrumentalism about the FEP is the only option. However, accepting that organisms do not literally embody the mathematics of the FEP does not ground the claim that scientific realism about FEP-models is false. To claim that it does is to commit the literalist fallacy. Bruineberg et al. (2021) focus on the ontological status of the Markov blanket formalism in the FEP. They argue that much of the literature on the FEP implies that organisms literally instantiate the mathematical structure of Markov blankets. They argue that such a use of the Markov blanket formalism conflates a model with its target system. They state that Markov blankets can be used in their original mathematical sense (what they call ‘Pearl blankets’). This usage they claim is philosophically innocent and consistent with instrumentalism; namely, as a potentially useful descriptive tool that does not have the aim of truthfully representing anything about target systems. However, they also consider that if one is to use the Markov blanket formalism in an ontological sense (what they call ‘Friston blankets’), the formalism in question must map directly onto target systems. This too is an instance of the literalist fallacy, because scientific realism about the Markov blanket implies (at most) that one can indirectly model target systems by using the Markov blanket formalism. Finally, Colombo & Palacios (2021) target the issue of ergodicity in FEP-models; namely, that one can realistically model biological systems as having an ergodic density. They deny that ergodicity captures properties of biological systems. However, modelling systems as ergodic is a modelling choice. It should not be mistaken as evidence for the claim that systems return to the exact same states in their phase space. To insist otherwise would be to commit the literalist fallacy.

The structure of the paper is as follows: In section two, we take up the question of what kind of model the FEP is. In section three, we consider whether FEP-models in virtue of being approximate and idealised models are incompatible with scientific realism. In the rest of the paper we discuss the central instrumentalist arguments for FEP-models. Section four focuses on inferring instrumentalism about FEP-models on the basis of variational free energy. Section five considers how the Markov blanket formalism has been used in the discussion over scientific realism. Section six looks at the topic of approximate Bayesian inference. Finally, section seven targets an argument suggesting that modelling biological systems as ergodic fails to model anything biologically realistic about such systems. All of these arguments commit the literalist fallacy. We conclude that scientific realism about FEP-models is a live and tenable option.

# **2. What Kind of Model is the FEP?**

In what follows, we follow Weisberg’s (2013) dual-aspect account of what comprises a scientific model: it has a particular (concrete or mathematical or computational) *structure* and an *interpretation* of that structure (see also Andrews 2021).

The question now is whether the FEP, given Weisberg’s account, can be thought of as a scientific model. This turns out to depend on the *practice* of modelling involved in the FEP. Say one builds amodel of a yet-to-be-built bridge in some appropriate scale. Here, the model would have a material or *concrete* structure (Weisberg 2013). The FEP does not offer anything comparable in terms of concrete structure. Instead, the FEP is best understood as a *mathematical* structure. It is a structure that expresses the dynamics of any system in terms of equations for random dynamical systems with a Markov blanket. On the basis of this, the dynamics of external states, internal states and blanket states are captured by a gradient ascent on what is called an ‘ergodic density’ (Palacios et al. 2020). All of this is mathematics and can be applied to any random dynamical system (i.e. any dynamical system whose equations of motion have an element of randomness due to noise). This would be part of the mathematical structure upon which the FEP is grounded (see Friston 2019 for full details).

Andrews (2021) incisively distinguishes a number of different ways the FEP, as a mathematical framework, can be formulated as a scientific model. Here we focus on three possible interpretations: targetless models, generalised models and target-directed models. This conceptual terminology is developed in detail by Weisberg (2013), yet fruitfully imported into the FEP literature by Andrews (2021). The first option we consider is to describe the FEP as an instance of what in the modelling literature is called a *targetless model*. In targetless modelling, the “object of study is the model itself, without [direct] regard to what it tells us about any specific real-world system. This type of modelling is most akin to pure mathematics.” (Weisberg 2013, p. 129)

There is more to be said about models in general, and the FEP especially. In both the concrete and mathematical case, the model structure must itself be *interpreted* by someone as was the case with our earlier example of a scale model of a bridge. The FEP, as a mathematical structure, is a set of axioms. The axioms licence an interpretation of characteristic states of being (e.g., homeostatic states). Terms such as *free energy minimisation* and *maximisation of model evidence* can be given mathematical precision and used to describe how organisms are able to return to preferential states (e.g., maintaining core body temperature). Therefore, the FEP comprises both a mathematical structure and an interpretation of this structure. This would be consistent with Weisberg’s view of scientific models.[[2]](#footnote-2) Andrews points out that the FEP falls under the larger grouping of approaches to modelling without a *specific* target (in the sense of Weisberg 2013). We think the FEP is a good example of what Weisberg calls *generalised modelling*. The target in this form of modelling is not specific; it is more abstract. For example, a generalised model of sex reproduction will not say anything about sex reproduction in Australian wombats.

There will not be any specific species modelled by a generalised model. Similarly, when FEP-models use the Markov blanket formalism to derive a proof of concept of how systemic states can be differentiated from environmental states (a necessary requirement for existence), the model one gets is a general model. It concerns a general (and statistical) delineation problem and does not refer to any specific system.[[3]](#footnote-3)

In contrast to models without a target (e.g., a targetless model), a target-directed model has a specific target system it represents (Weisberg 2013). Or, the modeller has a specific target system in mind - e.g., maze navigation in rats or chemotaxis in Escherichia coli. The FEP becomes a target-directed model once implemented by a process theory - e.g., *active inference* (Friston et al. 2017). Unlike the mathematics of the FEP, the process theory provides a possible (mechanistic) story about how the FEP is implemented in real-world, target systems (see Tschantz et al. 2021 for a FEP-model of chemotaxis). Once a process theory of the FEP is proposed, the map problem arises.

We suggest then that the FEP can be thought of as a generalised model. The mathematics of the FEP can be used to construct active inference models of target systems and their behaviour. We suggest that the resulting models are best described as target-directed. The FEP provides a mathematical structure, which is given an interpretation via active inference. Second, we can also distinguish between active inference models based on the FEP and the target systems such active inference models indirectly represent. The map problem arises only when one seeks to understand if, and how, active inference models indirectly represent target systems. It is this relation we focus on in this paper: the relation between a model and how it relates to a target system.

Should we conceive of the process theory as an indirect representation of the true behaviour of a target system? There is good reason to think that active inference models based on the FEP indirectly represent their target systems. For example, Parr & Friston (2017) show how an active inference model of working memory can be correlated with neurophysiology, and roboticists are now able to use active inference models enabling the construction of control, planning and learning in artificial agents (Lanillos et al. 2021).

A final reminder, when we discuss the map problem in relation to the FEP, we do so only in the context of the FEP as a target-directed model.

# **3. Idealisation, Scientific Realism and the Free Energy Principle**

In this section, we shall introduce several key issues that will inform the discussion of the instrumentalist arguments to come: idealisation and approximation. As we shall see, FEP-models are idealised and approximate models. What does this tell us about scientific realism with respect to such models?

Idealisation and approximation are seen by many as central to scientific progress. Yet, there is no consensus on how to understand the relation between the concepts of idealisation and approximation. What certainly *can* be said is that idealisation involves a deliberate simplification or distortion of some phenomenon of interest into a scientific model, or theory. In FEP-models, the variational free energy function is introduced to make a computationally intractable problem tractable. It is a way of deliberately simplifying a mathematical problem.[[4]](#footnote-4) Approximation involves representing some target system inexactly. In FEP-models, action, perception and decision-making can be cast as maximising model evidence under a generative model. This makes it possible to treat state transitions in terms of Bayesian inference. Yet, this is strictly speaking to represent target systems inexactly, because target systems under FEP-models are only taken to approximate Bayesian inference.

Here we focus on idealisation (and return to approximation later).[[5]](#footnote-5) Idealisation looks to present a problem for any kind of scientific realism. Consider this formulation of scientific realism by Godfrey-Smith (2003): one “actual and reasonable aim of science is to give us accurate descriptions (and other representations) of what reality is like. This project includes giving us accurate representations of aspects of reality that are unobservable." (2003, p. 176) Idealisation does not look like a strategy for delivering accurate representations of the kind the scientific realist demands.

Klein (2018) has suggested in passing that the FEP is best thought of as Galilean idealisation. He describes the FEP as being:

“...literally false, but with some understanding gained via over-simplification. Such idealizations can often be elaborated to be true of particular systems, and those elaborated models—which often look very different from the original model—can have considerable explanatory power. But if this is the case, then it is worth keeping in mind that FEP is a starting point from which one might develop explanations, and that its defence would ultimately rest on the empirical adequacy of detailed models which spring from it. Simplicity does not count in its favour, for FEP is simple in the way that friction-free planes and infinite populations of bunnies are simple: that is, a deliberate simplification, which buys scientific fruitfulness at the cost of literal truth.” (Klein 2018, pp. 2253-2254)

Idealisations may involve a distortion of something to be understood in order to gain a better understanding of it. A Galilean idealisation is the simplification or distortion of something into a model in order to turn a computationally intractable problem into one that is tractable (McMullin 1985) - e.g., the variational free energy function in FEP-models.

Is Klein right to say of Galilean idealisations, in general, and with respect to the FEP, specifically, that such idealisations are literally false? We do not think so.

First, Weisberg (2007) draws our attention to the fact Galilean idealisation is consistent with scientific realism. He says of this kind of idealised model that it is the most straightforward type of idealised model compatible with scientific realism. Accordingly:

“...the Galilean idealizer does aim to give complete, non-distorted, perfectly accurate representations. In order to accommodate the possibility of Galilean idealisation, scientific realists need to understand that achieving accurate representations of complex phenomena is an ongoing process. Even when the short term practice involves the willful introduction of distortion, the long-term aim can still be to give an accurate representation of what reality is really like. Thus scientific realism is perfectly compatible with Galilean idealisation, if the realist aim is understood to be long term or ultimate.” (2007, p. 657)

Second, it does not follow that if a model is a Galilean idealisation it is *literally false*, in the sense of being *completely* false. Galileo, in his work on projectile motion or the diurnal rotation of the Earth, made use of models with *mixed claims*: some descriptions of entities should be taken as literally true (e.g., projectiles, the Earth, and so on), while other descriptions are better construed as *concrete* but *non-actual* or *fictional* (e.g., a frictionless plane is a concrete object but does not exist). Galilean models idealise by positing non-actual entities with respect to target systems to solve particular problems. FEP-models do the same. However, as with Galileo’s models, FEP-models are not literally false. FEP-models idealise but they are not exhaustive idealisations in the sense of being complete distortions of target systems.

What does this tell us about scientific realism regarding FEP models?[[6]](#footnote-6) One way of describing instrumentalism would be for a model to merely result in a good and useful *phenomenal model*, even if it turns out to be wrong about underlying mechanisms and/or target systems. An example of this is Ptolemaic astronomy. One certainly does not have to be a realist about Ptolemaic astronomy. As we are considering Galilean idealisations in the discussion about the FEP, issues about realism come up due to the map problem. Unlike the field of astronomy at the time of Ptolemy, target-directed formulations of the FEP under active inference seek to understand the mechanics of target systems.

Klein goes on to claim that Galilean idealisations ‘can often be elaborated to be true of particular systems, and those elaborated models—which often look very different from the original model—can have considerable explanatory power.’ This strikes us as correct. Indeed, this is what an *implementation* of the FEP aspires to in active inference. It is in this precise formulation of active inference models based on the FEP that the map problems arise. Klein’s final point is well-taken; namely, the “FEP is simple in the way that friction-free planes and infinite populations of bunnies are simple: that is, a deliberate simplification, which buys scientific fruitfulness at the cost of literal truth” (Klein 2018, p. 2254). This much may be correct in the short term. It is the long-term goal of FEP-models to indirectly represent the true behaviour of their target systems. This is the very reason for why we think Galilean idealisation can be in the service of scientific realism, given that Galilean idealisers aspire, in the long run, to provide a more accurate description of target systems. There is no reason to think this is not the case for researchers in the active inference literature. The aspiration to construct realistic models must be appreciated to be a long-term goal of a theory. FEP-models need not be truth-producing just yet, or need not be completely truth-producing just yet.

A slightly different concern is that model building *simpliciter* implies instrumentalism. It would suggest that model building is ultimately a matter of convention; not discovery. Yet, following Williamson, we think:

“that would be a very naïve conclusion to draw … If we are investigating a complex reality out there, it is not at all surprising that it is sometimes best to use a sophisticated, indirect strategy, to ask questions quite subtly related to the overall aims of the inquiry. To build a model is just to identify by description a hypothetical example which we intend to learn about in hope of thereby learning about the more general subject matter it exemplifies. Nothing in that strategy is incompatible with a full-bloodedly realist nature for the scientific inquiry.” (Williamson 2017, pp. 3-4)

In summary, scientific models such as active inference models - in order to be compatible with scientific realism - need not necessarily truthfully describe their targets. Even if a scientific model deliberately introduces distortions into its model of some target system, scientific realism need not be ruled out. Indeed, even if a scientific model adds into its structure fictional elements for instrumental gain, this still does not get scientific realism of any sophistication off the table (Godfrey-Smith 2009).

We now turn to assess each of the arguments for an instrumentalist interpretation of FEP-models in detail.

# **4. Argument One: Variational Free Energy**

It is reasonably straightforward to think of scientific models as positing abstract entities; or, as positing entities that do not map onto target systems. The centre of mass of the solar system, a frictionless plane, a path of least action are all examples. In the context of FEP-models, the *variational free energy* notation is a good example of a theoretical entity that can be given a concrete mathematical specification, although target systems do not literally reflect the mathematical structure of the variational free energy notation.

Variational free energy is an information-theoretic construction used to *compute* how organisms are able to resist decay by positing variational free energy as an upper bound on surprise. Under FEP-models, for an organism to exist it must keep its states (e.g., homeostatic states) within certain bounds. Or, it must maintain a low conditional entropy over its internal states (Corcoran et al. 2021). FEP-models invoke an information-theoretic term to explain how this is achieved: *surprise*. This term allows a quantification of the *improbability* of some outcome (e.g., some sensory data). An important aspect of surprise is that it is conditional on the phenotype of an organism. A standard example is that the quantity of surprise goes up and down relative to whether a fish samples a sensory state on land or in its natural aquatic milieu. FEP-models state that by minimising the surprise associated with particular sensory states, an organism is able to keep the entropy of its states low (and effectively survive), since entropy converges with long-term surprise.

Here is the important point for instrumentalists about FEP-models (e.g. Friston 2019; van Es 2020). Surprise is widely recognised as being *computationally intractable*. The main reason for this has to do with having to summarise over the joint probability distribution involving how external states cause sensory states. Computing the surprise associated with sensory observations would require complete knowledge of the external dynamics resulting in sensory input (Friston 2010). Such a computation is intractable. This is why variational free energy is relevant. It is associated with a proxy for the quantity of surprise elicited by sensory data, and defined as a *functional*: it is a function of the function of sensory and internal states. It can be employed to reduce surprise precisely because it is defined as always being equal to or greater than surprise (Friston 2019). Variational free energy is thus an *abstract* entity enlisted into the FEP to provide a mathematical description of how organisms are able to maintain a low entropic distribution over constituent states.

Friston says that the FEP is “a mathematical formulation of how adaptive systems (that is, biological agents, like animals or brains) resist a natural tendency to decay,” (Friston 2010, p. 1). Crucially, according to Ramstead et al. (2020), “this means that internal and active states will look as if they are trying to minimise the same quantity; namely, the surprisal of states that constitute the thing, particle, or creature.” (2020, p. 21) Or, as Ramstead et al. (2019) also put it, “any system that avoids surprising exchanges with the world (i.e., surprising sensory states) will look as if it is predicting, tracking, and minimising a quantity called variational free energy, on average and over time.” (2019, p. 320) This suggests that what is implied is that “the system does not actually predict, infer, track or minimize a quantity called variational free energy, but it merely looks *as if* this is what it is doing. The probabilistic model merely tracks certain real statistical relations in the organism-environment system.” (van Es 2020, p. 321) Since target systems do not literally reduce this quantity, some of these authors conclude that scientific realism about FEP-models is false.

There are at least two readings of the *as if* claim about minimising variational free energy in the literature. One is the claim that because target systems do not minimise variational free energy, but merely looks as if they do so, scientific realism about FEP-models is false (van Es (2020). It is this formulation of FEP-models we shall focus on here, because it is this formulation that is directly relevant to the map problem. The other reading of the *as if* formulation of FEP-models is consistent with scientific realism given a particular understanding of active inference in adaptive behaviour (Ramstead et al., 2019, 2020). We shall not address this second reading in detail, primarily because it does not raise the map problem - it is a set of claims about the target system.[[7]](#footnote-7)

Variational free energy is an idealised notation in FEP-models because it is not literally true that target systems minimise this quantity. Nevertheless, it raises some quite interesting modelling issues and questions. For example, it can be used to “quantify and simulate self-evidencing [i.e., maximisation of model evidence].” (Friston 2019, p. 85) It prompts the question of whether “self-organisation approximate Bayesian inference – or does Bayesian inference approximate self-organisation? (Friston 2019, p. 85) These are modelling questions that may lead to new discoveries about target systems.[[8]](#footnote-8) We have more to say about this in section six. Here we want to focus on the following: that the status of variational free energy as an idealised entity *has lent false credibility* to instrumentalist claims about FEP- models.

Here is how the first reading of the *as if* claim about FEP-models leads some to affirm instrumentalism about the FEP. If taken literally, FEP-models cannot be true. Alternatively, FEP-models may not be understood literally. However, if FEP-models should not be understood literally, then scientific realism about FEP-models is false. Or, so it seems to those favouring instrumentalism about FEP-models. This apparent dilemma for the scientific realist rests upon a misunderstanding of scientific realism. Instrumentalism about FEP-models does not follow from the fact that FEP-models do not provide descriptions of target systems that are literally true. Or, differently put, one cannot justify instrumentalism about FEP-models because such models are idealised models - models that introduce distortions into models of target systems. In fact, scientific realists have always allowed that sophisticated models are highly partial and idealised, and yet that their predictive prowess constitutes prima facie grounds for concluding that they function to accurately describe aspects of target phenomena.

FEP-models comprise an indirect representation of a target system, even if it involves the use of abstract entities. It is an idealised approach to representing complex or unknown processes in the world. It is standard practice to view scientific models as *indirect representations* of real-world, target systems (Weisberg 2006). Furthermore, most theoretical models are composed of a set of *mixed claims* (Psillos 2011). This means that the model will posit, if true, the presence of “both OK-entities (such as electrons and their ilk) and supposedly non-OK-entities (such as numbers … or theoretical ideals.” (Psillos 2011, p. 6) The FEP is such a model. It puts forward OK-entities (such as neurons, reflex arcs, hierarchical structures in the brain, and so on) and non-OK-entities (such as the variational free energy notation), where non-OK-entities must be understood in terms of not being literally true of target systems.

This raises an important question: what is the status of such *non-OK entities* such as variational free energy. Some proponents of the instrumentalist reading of the FEP say that the claim that organisms minimise free energy is a *useful fiction* - it is an ‘as if’ story; not a literally true story. It is tempting to think that if a claim is not literally true of a target system, but is nevertheless explanatorily useful, then this claim must have the status of a fiction. It is this *fictional status* of variational free energy that seems to motivate instrumentalism about FEP-models.

However, taking variational free energy to be a useful fiction is not incompatible with a scientific realist interpretation of FEP-models. We noted above that implicating non-OK entities in model building is part and parcel of the process by which descriptions of models are constructed - infinitely large populations in biology, ideal gases, mass-points, state space, attractor points, perfectly isolated systems, and so on, are examples. Variational free energy falls within the same class of fictional entities. It is a mathematical notation that is not actually implemented by any target system.

Godfrey-Smith (2009) notes three important properties of fictional entities in science. First, *hypothetically*, were such entities to exist, they would be entities located in space-time. They would allow for actual, not hypothetical, interventions. Second, fictional entities have *investigative* properties; they are the common property of a community of researchers - e.g., the FEP community, which inherits many of its notations from other areas such as statistical physics and machine learning. This means they can be “investigated collaboratively [and] surprising properties might be uncovered by one investigator after being denied by another.” (2009, p. 102) Finally, given their hypothetical *and* investigative properties, “their status, though not their role, [...] seem analogous to the fictions of literature.” (2009, p. 102) The crucial point here is that by means of theorising with fictional entities, one may learn about the world - both with respect to observable entities and unobservable structures. This is enough for scientific realism, and it is sufficient vis-a-vis models generated through the FEP: it posits fictional entities in its modelling of target systems in order to learn about such systems.

It might be objected that works of fiction do not tell you anything about the world. So, fictions cannot do the needed work to ground scientific realism - not even in the case of FEP-models. Here, again, the work on the relation between models and fictions in science by Godfrey-Smith (2009) is constructive. Briefly, since we will return to this issue in section five and six, one might say that certain parts of a theoretical model are fictional entities (e.g., variational free energy), and that these entities have different *similarity* relations to target systems. Specifically, biological systems that are able to minimise surprise will *appear* to minimise their variational free energy. Here is a case of similarity between the model and the target system. Godfrey-Smith (2009) puts the general view as follows: “model systems are fictional things which have various similarity relations to real-world systems. We learn about the former, and use that knowledge to illuminate and adapt us to the latter.” (2009, p. 108) In the very same way, investigations of how variational free energy is minimised in a model allows for insight into how surprise (or long-term entropy) is minimised in target systems. Fictional entities can be seen as laying a path towards understanding the dynamics of real-world, target systems. It is this feature that allows fictional entities in model construction to tell you something about the world of target systems. This is all one needs for a realist interpretation of FEP-models (see Beni (2022) for work that further unpacks our claim about similarity between FEP-models and target systems).

# **5. Argument Two: Markov Blankets**

We now consider work by Bruineberg et al. (2021) on the Markov blanket formalism underwriting FEP-models. They argue that the use of the Markov blanket formalism in the literature on the FEP often takes the formalism (the map) to literally be a property of the territory.

The Markov blanket concept originates with Pearl (1988) in his work on probabilistic reasoning and Bayesian networks. In probabilistic networks, Markov blankets are used to model probabilistic relations between nodes or variables: e.g., nodes A and B can be modelled as conditionally independent from one another in virtue of a third node, C. In this case, C can be said to ‘shield’ or ‘separate’ A from B, and vice-versa. According to Beal (2003), the “Markov blanket for the node (or set of nodes) A is defined as the smallest set of nodes C, such that A is conditionally independent of all other variables not in C, given C.” (2003, p. 18) The key point here is that once a Markov blanket has been identified for any given node, e.g., A, this captures all the relevant information needed to *infer* the state of A. Markov blankets can be used in order to model (in)dependencies between different variables, which allows for an approach to probabilistic reasoning under uncertain circumstances. Bruineberg et al. (2021) call Markov blankets of this kind *Pearl blankets*.

Under the FEP, this formal model of identifying conditional independence between nodes in a network is *interpreted* in a specific way. That is, once a Markov blanket has been identified for a living system, the blanket states are modelled as active and sensory states, separating internal (organismic) states from external (environmental) states. Bruineberg et al. (2021) call Markov blankets of this kind *Friston blankets*. Unlike Pearl blankets, Friston blankets work to describe a real-world boundary demarcating an organism from its environment, and vice-versa. According to Bruineberg et al. (2021), the use of Friston blankets to draw a distinction between organism and environment is not licensed by appeal to the mathematical structure of Pearl blanket. Hence, Bruineberg et al. (2021) finish their article by providing FEP researchers with a choice:

“the considerations presented in this paper leaves the FEP theorist with a choice. One can accept a rather technical and innocent conception of Markov blankets as an auxiliary formal concept that define[s] what nodes are relevant for variational inference [= Pearl blankets]. This conception is admittedly scientifically useful but has not yet led to any philosophically interesting conclusions about the nature of life or cognition. Alternatively, one can import a number of stronger metaphysical assumptions about the mathematical structure of reality to support a realist reading, where the blanket becomes a literal boundary between agents and their environment [= Friston blankets]. Such a strong realist reading cannot be justified by just ‘doing the maths’, but rather needs to be independently argued for, and no such argument has yet been offered.” (2021, p. 53)

The problem with this kind of argument should now be very clear: accepting some important, or even fundamental, link between Markov blankets and organism-world boundaries does not entail accepting the further literalist claim: that the formal and mathematical structure of a Markov blanket (the map) literally is the boundary (the territory). Those working with *Friston blankets* need not accept the literalist view that Bruineberg et al. (2021) attribute to them. This was the point we made above that scientific models are indirect representations of target systems.

Bruineberg et al. (2021) make a good deal out of the fact that the shift from Pearl blankets to Friston blankets requires *an interpretative step*. It requires interpreting Markov blanket states in terms of sensory and active states. But, any kind of interpretation is done by a theorist, rendering the identification of Markov blanket states arbitrary. The point about interpretation is fair. It is another thing entirely to infer that interpretation implies arbitrariness. Nevertheless, science is unlikely to progress in the absence of interpretation. First, any application of a model to a target system requires interpretation of the model for it to be a modelof the target system. This is the case for any kind of model, whether it be concrete, mathematical, computational or some other kind of model. Recall our example of the scale model of a bridge at the start of the paper: even a scale model of a bridge must be interpreted as a model of a bridge for it to be meaningful for those using it. As a matter of fact, interpretation is also part of working with Pearl blankets. Importantly, interpretation does not imply arbitrariness. Interpretation does not rule out scientific realism about the use of the Markov blanket formalism in the application of FEP-models.

A useful reminder of the necessity of interpretation in science, can be found in a classical discussion on the role of *hypotheses* in science by the 18th Century scholar, Emilie du Châtelet. In her *Foundations of Physics*, she says the following of hypotheses:

“There must be a beginning in all research, and this beginning must almost always be a very imperfect, often unsuccessful attempt. There are unknown truths just as there are unknown countries to which one can only find the good route after having tried all the others. Thus, some must run the risk of losing their way in order to mark the good path for others; so it would be doing the sciences great injury, infinitely delaying their progress, to banish hypotheses as some modern philosophers have.” (1740, p. 147)

For the scientist to construct a hypothesis they must ask questions, led by their explanatory interests. Model building involves interpreting structures in the world in a meaningful way. If this is on the right track, then science without any kind of interpretation, without any kind of explanatory or interest on behalf of researchers is a false idealisation of the scientific method. Moreover, there is no need to think, or so we submit, that these features of the scientific method create any problem for scientific realism.

Finally, Bruineberg et al. 2021 argue that the scope of the FEP formulation is “so broad that it is inadequate to pick out only living or cognitive systems.” (2021, p. 48).

Therefore, they contend, the claim that the FEP unifies biology and cognition is problematic. The idea is that this is a problem for scientific realism with respect to the FEP. It is true that the FEP as a mathematical structure does not cut any interesting biological or cognitive joints (see e.g., Kirchhoff 2018; Kirchhoff et al. 2018). Yet, explanatory scope issues are mute with respect to scientific realism. Or, differently put, one cannot derive a claim about antirealism by appealing to the explanatory reach of the FEP. One can only establish that the FEP applies to more systems than biological systems.

We end this tour into the world of blankets with a further reflection and qualification on *literalism*. A scientific realist might admit that in certain circumstances, there will be local reasons to posit non-OK entities and give them a literal interpretation. But, in such cases the scientific realist will not be providing a literal interpretation of these abstract entities across the map-territory relation. Consider what Psillos (2011) says of the Carnot engine: “The model of a (fully reversible) Carnot engine is such that it cannot represent exactly and accurately any worldly engine. This was known to Sadi Carnot himself—as well as to anybody else—and this knowledge might be enough to justify taking the Carnot engine as a fiction.” (2011, p. 6)

It is obvious that the Carnot model is a model with *mixed claims*. We addressed this above, and will say no more here. Yet, it is worth highlighting that the scientific realist might take literally the theoretical description of the (fictional) Carnot engine. In discussions about FEP-models, the scientific realist might take literally the theoretical description of the Markov blanket formalism, without endorsing the additional claim that the formalism itself literally is the target boundary being modelled.

This brings up an important issue to which we shall now turn: *approximation*. As we understand it, the Markov blanket formalism itself is not literallytrueof target systems. It is an approximate way of representing the boundaries of target systems. The scientific realist may endorse the claim that the theoretical description is literally true, but only approximately true of the target system. This leaves it open to provide further details about the model and its relation to target systems. We now consider this issue with respect to Bayesian inference and generative models in FEP-models.

# **6. Argument Three: Approximate Bayesian Inference**

It is common to read that instrumentalism about FEP-models is motivated by appeal to free energy minimisation being an approximation of Bayesian inference (see e.g., van Es & Hipolito 2020; van Es 2020).

In section four, we considered the status and role of variational free energy in FEP- models. The relevant issue about literalism versus approximation arises once questions are asked about how organisms minimise free energy. The usual proposal is that free energy minimisation can be shown to be equivalent (under certain mathematical assumptions) to Bayesian inference given a generative model. A generative model is a *probabilistic* specification of how some kind of data might have been generated. According to Parr & Friston, a generative model “expresses prior beliefs about unobserved hidden states [i.e., causes of sensory input], the probabilistic dependencies between these states, and a likelihood function that maps hidden states … to sensory data …” (2018, p. 2) A generative model can be used to predict new data. It can be used to infer the hidden states that may have caused the observed data (Beal 2003). This allows a Bayesian rendition of active inference under the FEP; namely, that internal, sensory and active states of an organism can be understood as engaging in optimising posterior beliefs over a (generative) model as new evidence (sensory input) is generated.

Here the instrumentalist can make their case. Very few think that systems such as brains *literally* compute Bayes’ rule - the set of computational steps used to update beliefs given new evidence under that particular framework. Insofar as brains *do* such things as Bayesian inference, they do *approximate* Bayesian inference. To suggest otherwise would be a clear case of conflating the mathematics with the territory (cf. Andrews 2021). Hence, the FEP, even when given a Bayesian articulation, is not the claim that organisms perform optimal or literal Bayesian inference to minimise surprise. The FEP is the claim that the minimisation of variational free energy conforms to an *approximation of Bayesian inference*. It is the nervous system that can be said to engage in approximate Bayesian inference, given that neuronal dynamics seek to anticipate sensory input (or, seek to maximise the likelihood of sensory observations). The anticipatory cascades are a good approximation of the true posterior so long as surprise is kept to a minimum.

Norton (2012) defines ‘approximation’ as inexact descriptions of a target system (2012, p. 207). Since FEP-models employ inexact descriptions of target systems, they are not literally true of their target systems. The use of approximations in FEP-models may therefore be taken to lend support to instrumentalism about such models. Such an inference however again relies upon the literalist fallacy, since nothing about approximation shows that scientific realism is false with respect to FEP-models.

A small proviso to the above paragraph. One must be cautious to distinguish the notion that FEP-models feature approximations of various kinds from the distinct notion that the respective target systems themselves approximate a form of (variational) Bayesian inference. One might hold that FEP-models really describe the organism as approximating Bayesian inference, and that the organism does indeed literally approximate Bayesian inference but not in the sense of how a computer- based model would do this (the organism or its central nervous system presumably does not allocate numbers across a probability space). This is very much how Hohwy approaches the issue here:

“The key point is that approximate inference is not just like exact inference except with approximate values, rather the ‘approximation’ is the minimization of the KL-divergence [the difference between posterior and recognition densities that is minimised during the minimisation of variational free energy]: an approximation of the states of the system to the states that it would have if it were indeed computing exact inference. This means that it is correct to say that such a system is literally doing ‘approximate inference’ even if it does not literally do ‘inference’ in the sense of ‘computations over probability distributions’.” (2020, p. 17)

Hohwy’s point is that it can be true to claim that brains approximate Bayesian inference even if brains do not literally compute belief updating schemes such as Bayes’ rule. If the claim that brains engage in approximate Bayesian inference is true, then it is possible to say that there is a *similarity* between models in cognitive neuroscience and their target systems. The similarity between Bayesian models and the brain allows cognitive neuroscientists to gain further insights into the functional and structural organisation of the brain. This is consistent with scientific realism. As Giere (1988) puts it (in a different discussion):

“One way science advances is by discovering new aspects of the world, that is, new respects in which models might resemble the world. Science also advances by discovering some respects in which similarities between model and world are not as commonly thought. Neither sort of advance, however, is inconsistent with … realism.” (1988, p. 107)

Of course, logically speaking, everything is similar to everything else in some sense. Yet, this does not prevent an assessment of the relevant kinds of similarities that might exist between an approximate model and its target system.

Under FEP-models, the similarity between a scientist's generative model and the dynamics of the brain turns on the idea that the neuronal dynamics *conform* to the scientists’ model. What this means is that if both neuronal dynamics and the scientific model succeed in reducing surprise, they both converge on the following: the ability to keep a low conditional entropy over their constituent states. More specifically, in a recent review of the field, Isomura (2021) concludes that progress in theoretical neurobiology demonstrates that standard neural networks perform variational Bayesian inference under the form of a generative model. This is another way of conceptualising the issue of similarity between models and target systems, since it “demonstrate[s] that standard neural networks - comprising biologically plausible neural activity and plasticity models - can perform … inference.” (Isomura 2021, p. 1) Note that this connects nicely with Hohwy’s (2020) claim that “it is correct to say that such a system is literally doing ‘approximate inference’ even if it does not literally do ‘inference’ in the sense of ‘computations over probability distributions’.” (2020, p. 17)

A related question to ask is: what does working with generative models enable scientists to do? Note that we are here shifting perspective from the target system itself to the theoretical model used by the scientist. According to Turner & Zandt (2018), new Bayesian techniques using approximate methods are making it “possible to fit these … models to data. These techniques have even allowed simulation-based models to transition into neuroscience, where tests of cognitive theories can be biologically substantiated.” (2018, p. 1) In the FEP literature, this sort of work is starting to emerge. Generative modelling in FEP-models is being used to explore how biological systems such as the brain are able to anticipate sensory observations. For example, Parr et al. (2019) investigate generative models under active vision. Of the significance of this work, they say:

“Using dynamic causal modelling to quantify changes in effective connectivity, we found evidence that the coupling between the dorsal and ventral attention networks changed during the saccadic interrogation of a simple visual scene. Intuitively, this is consistent with the idea that these neuronal connections may encode beliefs about “what I would see if I looked there”, and that this mapping is optimized as new data are obtained with each fixation.” (2019, p. 1)

One might still try to press the point: there are models that cannot be understood literally, even if they are useful models; conversely, there are models that cannot be understood literally and the reason is that they are not explanatorily useful or fruitful. Are FEP-models explanatorily useless? We do not think they are. Active inference models are now being used productively to gain insight into a plethora of different phenomena: decision-making under uncertainty (Friston et al. 2012), optimal control (Catal et al. 2019), psychopathology (Schwartenbeck et al. 2015), active scene construction (Mirza et al. 2016), electrophysiological responses (Friston et al. 2017), and so on (see Da Costa et al., 2021 for a detailed overview of different applications of FEP models).[[9]](#footnote-9)

We can see from this example how cognitive neuroscientists are using the FEP to construct generative models that they intend to be at least indirect representations of systems in the real world. The *indirectness* of models is a result of the *complexity* of target systems. Generative-model-based simulations allow for a reduction of the complexity in systems being modelled. Given what we have said here, we can make the following qualification: we do not infer from the idea that ‘some idealised models are approximately true’ to the claim that ‘FEP-models are idealised models and therefore approximately true’. Rather, we are making the claim that the FEP-models are idealised models, and that they are being used productively by a community of active inference researchers to understand targeted phenomena, and that such models are therefore approximately true of their target systems.

We have focused on the relation here between generative models as they are constructed in computational neuroscience and neural systems. Scientific realism is sometimes taken to imply that organisms encode or implement such a model, enabling them to navigate a dynamic environment. van Es (2020) argues against such a realist claim first by noting correctly that it is the “adaptive behaviour of the system that implements or instantiates a generative model”. It is the organism’s adaptive behaviour that “brings forth the conditional dependencies captured by the generative model” (van Es 2020, p. 7; both quotes). van Es (2020) goes on to argue that it is adaptive behaviour that does the work of minimising free energy, and the generative model is “merely a scientific construct that captures real statistical relations in the world.” (2020, p. 318) We agree. However, we take these points to illustrate the similarity we have argued for above between the properties of the generative model and adaptive behaviour, such that one can capture *real statistical relations in the world* by means of generative modelling. It is this crucial point about the relation of relevant similarity between the generative model of the scientist and the dynamics of the adaptive behaviour of organisms that is missed by van Es and others defending instrumentalism about FEP-models

# **7. Argument Four: Ergodicity**

We now turn to consider the final argument for instrumentalism about FEP-models. This argument problematises a central commitment of such models: that organisms can be modelled as random dynamical systems with *bounded attracting states*, meaning that one can model systems that seek to maintain non-equilibrium steady states as having an *ergodic density*.

Random dynamical systems are systems whose states are subject to random fluctuations. This means that if one models a system as an *ergodic* system, the states of such a system will, after some amount of time, converge to what is called a random global attractor (i.e., a set of invariant states). Ergodicity refers to the “time average of any measurable function of the system converges (almost surely) over a sufficient amount of time. This means that one can interpret the average amount of time a state is occupied as the probability of the system being in that state when observed at random.” (Friston 2013, p. 2) Given this assumption, one can model the proportion of time a system spends in any region of its phase space as equivalent to the probability of such a system being in this region of its state space. An uncontroversial example is tossing a fair coin. With enough time spent tossing a fair coin, the probability of it landing on heads is equivalent to the time spent flipping the coin. Ergodicity concerning non-biological cases, such as coin tosses, is one thing. It is quite a different matter to assume ergodicity about biological systems. Colombo & Palacios (2021) argue that “while in physics one can ‘pre-state the phase space for target systems based on stable invariances and symmetries, historical processes studied principally in evolutionary and population biology…involve symmetry breaking, which makes phase spaces structurally unstable, ever-changing and unpredictable” (2021, p. 13). They argue on these grounds that the systems studied in biology are non-ergodic, calling into question the possibility of modelling biological systems in terms of random dynamical attractors. The FEP is taken to apply both to physical systems that can be modelled in these terms, and to biological systems that Colombo & Palacios (2021) argue do not admit of such modelling. They argue that the FEP achieves its generality at the expense of biological realism about its models.

Colombo & Palacios (2021) frame their discussion of trade-offs in terms of Levins’ (1966) framework in biology. Levins (1966) uses the term ‘realism’ in a way that is consistent with how scientific realism is, broadly speaking, understood in today’s philosophy of science. So, it is strange to find that this particular kind of trade-off is being used to make an argument against scientific realism about the FEP. With this in mind, we think that even if the FEP trades off realism (in the sense of Levins) for generality and mathematical precision, there is nothing about this that makes it problematic to endorse scientific realism about active inference models of target systems. More accurate representations of target systems can be gained by working to show how causal properties of target systems are reflected in FEP-models.

We suggest that ergodicity is best understood as a way of *interpreting* the behaviour of systems whose dynamics are subject to random environmental fluctuations. If one models a biological system as an ergodic system, it is possible to show that long-term surprise is entropy. This implies that minimising free energy results in keeping a low entropic distribution over internal states in ways that are interestingly similar to biological systems whose dynamics are anticipatory. Furthermore, it is now fairly common to weaken the notion of ergodicity. We have seen above how FEP-models require that populations *on average* tend to frequent the same kinds of phenotypic states. It is reasonably intuitive to think that biological systems tend to return to similar phenotypic states over time and that their adaptive behaviours depend upon them doing so. Body temperature is a good example, fluctuating around an average of 36.5C in humans. Ergodicity can in this weak sense be said to represent biological systems as an approximation of their true adaptive behaviours. We have seen above how the role of approximation in scientific modelling is no threat to understanding scientific models in realist terms.

# **Conclusion**

This paper has focused on the status of scientific realism concerning active inference models based on the FEP. In this context, many have found the view that FEP- models are idealised and approximate models of target systems a compelling reason to defend instrumentalism about FEP-models. We have argued that all the reasons provided (so far in the literature) for this instrumentalist rendition of FEP-models are fallacious. They commit, in one way or another, the *literalist fallacy*. This is the fallacy of accepting or affirming instrumentalism based on the claim that the properties of active inference models based on the FEP do not literally map onto real-world, target systems. In the end, we hope to have shown that a realist interpretation of FEP-models is a live and tenable option.

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1. See Mann et al. 2021 for a user-guide to the FEP. [↑](#footnote-ref-1)
2. One question some might have (thanks to an anonymous reviewer) is whether the FEP is a singular model or framework, or whether there is a family of things that fall under that label? We think this can be answered in two ways. First, one might treat FEP-models as falling under a philosophical family: there are representational and non-representational treatments of FEP-models; there are internalist and extended treatments of FEP-models; and so on. Second, one might treat FEP-models more scientifically, where there is a singular scientific framework currently evolving in the literature, with work being done to clarify the underlying mathematics - e.g., the shift from assuming ergodicity to giving a NESS density description of the FEP. Our focus in this paper is on the latter reading of FEP-models. [↑](#footnote-ref-2)
3. This view of the FEP as a generalised model turns out to interestingly diffuse an objection to the FEP by Raja et al. (2021). In their paper, Raja and colleagues argue that the generality of the FEP as a scientific model is premised on the general applicability of the Markov blanket (MB) formalism. However, Raja and colleagues object that the reason to use the MB formalism to set up a statistical boundary between things and their environment is that doing so provides the kind of structure needed to describe a system as engaging in Bayesian inference. The generality of the FEP thus trades on the assumption of the generality of the MB formalism. This is what Raja and colleagues label as “the Markov blanket trick”. We suggest however that once a distinction is made between a generalised model and its interpretation, there is nothing elicit in the assumption of the Markov blanket formalism, as Raja and colleagues imply. The making of this assumption is simply a part of the interpretation needed to make a target-directed model from the generalised model that the mathematics of the FEP underwrites. Our thanks to an anonymous reviewer for discussion of this point. [↑](#footnote-ref-3)
4. We deal with this issue in detail in section 4. [↑](#footnote-ref-4)
5. When defining idealisation as a ‘deliberate simplification or distortion of some phenomena of interest’ we follow McMullin (1985). When defining approximation as involving ‘representing some target system inexactly’ we rely on Norton (2012). For slightly different takes on these notions, see the work of Martin Thomson-Jones (2005) on idealisation and abstraction. [↑](#footnote-ref-5)
6. Thanks to an anonymous reviewer for pressing this point. [↑](#footnote-ref-6)
7. On the second reading of the *as if* formulation, the physical dynamics of a class of systems can be given an interpretation in terms of Bayesian decision theory. What is “as if” here is the ascription of agency and folk psychological states of beliefs to this class of systems. What underwrites such an ascription of agency is the interpretation of the behaviour of the system in terms of Bayesian decision theory. The physical system is “treated as though it were a rational sensorimotor agent” (McGregor 2017, p. 78). Such an interpretation of “as if” language is consistent with scientific realism. We are grateful to an anonymous reviewer for insisting on this point. To see the consistency, consider how active inference agents can be read in terms of Dennett’s (1996) reference to Popperian creatures. A Popperian creature is able to select hypotheses with the aim of pruning away inferior options to avoid fatal outcomes. In this sense, Popperian creatures have a kind of inner environment to select amongst possible actions. Popperian creatures are similar to agents described in terms of active inference, since active inference agents can infer the state of future observations on the basis of selecting possible action policies. Popperian creatures exhibit real patterns in their behaviour that can be described in terms of beliefs. [↑](#footnote-ref-7)
8. Williams and Drayson (forthcoming) discuss some of the misunderstandings that have emerged in the ongoing philosophical debate about whether said modelling enterprise should be construed as realist or instrumentalist. [↑](#footnote-ref-8)
9. We are working with the assumption that one line of evidence for the realist view is the idea that progressively better predictions about the workings of target systems are made possible by specific active inference models and that these constitute prima facie evidence for scientific realism, even if it turns out that much more work is still needed for anything like a solid understanding of target systems. [↑](#footnote-ref-9)