What does the free energy principle tell us about the brain?

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Abstract

The free energy principle has been proposed as a unifying theory of brain function. It is closely related, and in some cases subsumes, earlier unifying ideas such as Bayesian inference, predictive coding, and active learning. This article clarifies these connections, teasing apart distinctive and shared predictions.

1 Introduction

The free energy principle (FEP) states, in a nutshell, that the brain seeks to minimize surprise (Friston, 2010). It is arguably the most ambitious theory of the brain available today, claiming to subsume many other important ideas, such as predictive coding, efficient coding, Bayesian inference, and optimal control theory. However, it is precisely this generality that raises a concern: what exactly does FEP predict, and what does it not predict? Addressing this concern is not easy, because the assumptions underlying applications of FEP are malleable. Moreover, some of these assumptions are shared with other theories, and some are idiosyncratic; some assumptions are central to the theory, and others are *ad hoc* or made for analytical convenience.

This article systematically deconstructs the assumptions underlying FEP, with the goal of identifying what its distinctive theoretical claims are. As will become clear, FEP does not have a fixed set of distinctive claims. Rather, it makes different claims under different sets of assumptions. This is not necessarily a bad thing, provided we can verify these assumptions in any particular application and thus render the theory falsifiable.

Before proceeding, we must address a basic qualm with this approach. Some proponents of FEP might reasonably argue that identifying distinctive theoretical claims is pointless; the whole point of a unifying theory is to unify claims, not distinguish them. However, the fundamental issue here is not whether one theory is better than another, but how to assign credit and blame to different theoretical assumptions. If FEP fails to match the data, is that attributable to the assumption that the brain is Bayesian, or a particular algorithmic implementation of Bayesian inference, or particular assumptions about the probabilistic model? Only by answering such questions can we

understand the successes and failures of a unifying theory, devise suitable tests of its assumptions, and identify ways to improve the theory.

2 The Bayesian brain hypothesis

As a prelude to FEP, it will be helpful to briefly describe the Bayesian brain hypothesis (Lee and Mumford, 2003; Knill and Pouget, 2004; Doya et al., 2007), which can be expressed in terms that are more familiar to neuroscientists, and is in fact equivalent to FEP under certain conditions (as elaborated in the next section). The first claim of the Bayesian brain hypothesis is that the brain is equipped with an internal (or "generative") model of the environment, which specifies a "recipe" for generating sensory data (denoted by *d*) from hidden variables (denoted by *h*). This internal model may not be represented explicitly anywhere in the brain; the claim is that the brain computes "as if" it had an internal model. In order for the Bayesian brain hypothesis to have any predictive power, it is necessary to make specific assumptions about the structure of the internal model.

There are two components of the internal model that need to be specified. First, hidden variables are drawn from a *prior distribution*, P(h). For example, the hidden variable might be the orientation of a line segment on the surface of an object, and the prior might be a distribution that favors cardinal over oblique orientations (Girshick et al., 2011). Second, the sensory data are drawn from an "observation" distribution conditional on the hidden variables, P(d|h). For example, the hidden line orientation is projected onto the retina and then encoded by the firing of retinal ganglion cells. This encoding process might be noisy (due to stochasticity of neural firing) or ambiguous (due to the optical projection of three dimensions onto the two-dimensional retinal image), such that different settings of the hidden variables could plausibly "explain" the sensory data to varying degrees. These degrees of plausibility are quantified by the *likelihood*, the probability of the sensory data under the observation distribution given a hypothetical setting of the hidden variables.

The second claim of the Bayesian brain hypothesis is that the the prior and the likelihood are combined to infer the hidden variables given the sensory data, as stipulated by Bayes' rule:

$$P(h|d) \propto \frac{P(d|h)P(h)}{P(d)},\tag{1}$$

where P(h|d) is known as the *posterior distribution* and $P(d) = \sum_{h'} P(d|h')P(h')$ is known as the *marginal likelihood* (here we assume that all variables are discrete, but all the relevant calculations can be applied to continuous variables by replacing summation with integration). We can think of Bayes' rule as "inverting" the internal model to compute a belief about the hidden state of the environment.

The Bayesian brain hypothesis can be naturally extended to settings where an agent can influence its observations by taking actions. In the simplest variant, an agent takes actions in order to maximize *information gain*:

$$\mathcal{I}(a) = \sum_{d} P(d|a) \mathcal{D}[P(h|d)||P(h)],$$
(2)

where *d* now denotes a future observation, and *D* denotes the Kullback-Leibler (KL) divergence (also known as *relative entropy*):

$$\mathcal{D}[P(h|d)||P(h)] = \sum_{h} P(h|d) \log \frac{P(h|d)}{P(h)}.$$
(3)

The expression for $\mathcal{I}(a)$ is equivalent to "Bayesian surprise" (Itti and Baldi, 2009), and to the mutual information between *h* and *d* conditional on *a* (Cover and Thomas, 1991). Information maximization has been studied extensively in the cognitive psychology literature (Oaksford and Chater, 1994; Nelson, 2005; Tsividis et al., 2014). More generally, information maximization can be understood as a form of *active learning* that has been studied extensively in the machine learning and statistics literature (Settles, 2012).

Information gain maximization is a special case of Bayesian decision theory, where the utility of an observation corresponds to information gain, $u(d) = \mathcal{D}[P(h|d)||P(h)]$. If the observations are valenced (rewards or punishments), then utilities may reflect their goodness to the agent, who seeks to maximize the expected utility:

$$\mathbb{E}[u(d)|a] = \sum_{d} P(d|a)u(d).$$
(4)

This analysis can be generalized to sequential decision problems (see Dayan and Daw, 2008), where an agent's actions and observations unfold over time. Typically, the goal in sequential decision problems is to maximize discounted cumulative utility (return):

$$R(\mathbf{d}) = u(d_1) + \gamma u(d_2) + \gamma^2 u(d_3) + \cdots$$
(5)

where we have introduced a subscript denoting time-step and the bold notation $\mathbf{d} = [d_1, d_2, ...]$ denotes the time-series of observations. The discount factor γ down-weights future utility exponentially as a function of temporal distance. The expected return under the posterior is then defined analogously to expected utility:

$$\mathbb{E}[R(\mathbf{d})|\mathbf{a}] = \sum_{d} P(\mathbf{d}|\mathbf{a})R(\mathbf{d}),\tag{6}$$

where we now condition on a time-series of actions a instead of just a single action. More generally, we can allow actions to be a probabilistic function of the observations, $\pi(\mathbf{a}|\mathbf{d})$, known as a *policy*.

In sequential decision problems, an agent needs to trade off gathering information to reduce uncertainty (exploration) and taking actions that yield immediate reward (exploitation). This means that preferences for information will arise naturally in the sequential decision setting; they need not be built explicitly into the utility function.

There are several points worth noting here before moving on:

• Although the Bayesian brain hypothesis has received considerable support, there are numerous empirical deviations from its claims (e.g., Soltani et al., 2016; Rahnev and Denison, 2018). We will not evaluate the empirical validity of this hypothesis, focusing instead on more conceptual issues related to the free energy principle.

- The Bayesian brain hypothesis does not make any specific claims about the priors and likelihoods of an individual. Rather, the central claim concerns consistency of beliefs: a Bayesian agent will convert prior beliefs into posterior beliefs in accordance with Bayes' rule.
- The Bayesian brain hypothesis abstracts away from any particular algorithmic or neural claims: it is purely a "computational-level" hypothesis. All algorithms that compute the posterior give equivalent predictions with regard to the central claims of the Bayesian brain hypothesis, and likewise any neural implementation will give equivalent predictions. These equivalences do not hold, however, when we consider *approximate* inference schemes, which may systematically deviate from the Bayesian ideal. We will return to this point below.

3 The unrestricted free energy principle is Bayesian inference

The basic idea of the FEP is to convert Bayesian inference into an optimization problem (see Bogacz, 2017, for a tutorial introduction). This idea was first developed in physics, and later in machine learning, to handle computationally intractable inference problems. The key algorithmic trick, as we will see, is to restrict the optimization problem in such a way that it is not searching over all possible posterior distributions.

Assume we have available a family of distributions Q (discussed further in the next section), and we can choose one distribution $Q \in Q$ to approximate P(h|d). This leads to the following "variational" optimization problem:

$$Q^*(h) = \operatorname*{argmin}_{Q(h)} \mathcal{D}[Q(h)||P(h|d)].$$
(7)

The KL divergence is 0 when Q(h) = P(h|d). Thus, if P(h|d) is contained in the variational family Q, then the solution of the optimization problem yields the exact posterior: $Q^*(h) = P(h|d)$. This holds true when the variational family is unrestricted (i.e., contains all possible distributions with support on the hypothesis space).

Algorithmically, this optimization problem is not very practical because to compute the KL divergence we need access to P(h|d)—precisely the problem we are trying to solve! However, it turns out that one can reformulate this problem in a way that is more practical, based on the following identity:

$$\log P(d) = \mathcal{D}[Q(h)||P(h|d)] - \mathcal{F}[Q], \tag{8}$$

where $\mathcal{F}[Q]$ is the variational free energy:

$$\mathcal{F}[Q] = -\sum_{h} Q(h) \log \frac{P(d|h)P(h)}{Q(h)}.$$
(9)

The free energy is equivalent to the negative of the *evidence lower bound*, the more common term in the machine learning literature (Blei et al., 2017).

Note that the free energy only requires knowledge of P(h|d) up to a normalizing constant, since $P(h|d) \propto P(d|h)P(h)$. This is typically unproblematic, since we can often compute the prior

P(h) and likelihood P(d|h) of any particular hypothesis h. Critically, the identity above implies that minimizing the free energy is equivalent to minimizing KL divergence, since the two must balance each other out to match the marginal likelihood, which is fixed as a function of Q. Thus, minimizing free energy when the variational family is unrestricted is equivalent to exact Bayesian inference.

If FEP = Bayes, then we cannot distinguish its predictions from other asymptotically correct inference algorithms, such as Monte Carlo sampling, except when these algorithms are restricted in some way. Monte Carlo methods may, for example, be restricted in terms of the number of samples they generate or how they generate the samples. Optimization of free energy is typically restricted by placing constraints on the variational family, as we discuss next.

4 Restricting the variational family

If the hypothesis space is vast, then summing (or integrating) over all possible hypotheses to compute the free energy will be intractable. Thus, essentially all practical applications of free energy optimization make use of a restriction on Q that renders the optimization tractable (as will be discussed below). The important point for present purposes is that as long as $P \in Q$, the optimal Q^* will be equal to the posterior. Thus, FEP in its most general form is indistinguishable from Bayesian inference.

Practical applications of free energy optimization restrict Q in some way to make the problem tractable. These restrictions typically mean that the posterior is no longer contained in Q, and thus the distribution that minimizes free energy will deviate from Bayes-optimality: $Q^*(h) \neq P(h|d)$.

For example, the widely used "mean-field" approximation assumes that the posterior factorizes across components of h (i.e., dimensions of the hypothesis space):

$$Q(h) = \prod_{i} Q_i(h_i).$$
(10)

For example, if I'm trying to infer the posterior over the height and weight of an individual given their gender, I could assume that the posterior factorizes into Q(height|gender) and Q(weight|gender). Because the true posterior rarely factorizes, the mean-field approximation will produce systematic errors. For example, if the factorization is across a sequence of hypotheses, the posterior may be biased by the order of the data. Intriguingly, these errors can be discerned in human behavior (Daw et al., 2008; Sanborn and Silva, 2013).

When *h* is continuous, another common restriction is to assume that the posterior is Gaussian (Friston et al., 2007), parametrized by a mean μ and covariance matrix Σ :

$$Q(h) = \mathcal{N}(h; \mu, \Sigma). \tag{11}$$

These parameters are then chosen to minimize the free energy, typically by gradient descent. The Gaussian approximation can be motivated by the "Bayesian central limit theorem," which states that the posterior is approximately Gaussian around the mode when the amount of data is large

relative to the dimensionality of *h*. It can also be generalized to mixtures of Gaussians to approximate multimodal posteriors (Gershman et al., 2012).

One challenge facing applications of the Gaussian approximation is that the free energy is not, in general, tractable (except in the case where the exact posterior is Gaussian). To deal with this issue, a common technique, known as the *Laplace approximation*, is to use a Taylor series expansion to "linearize" the free energy around the posterior mode. This replaces the nonlinear free energy with a linear function tangent to the mode, rendering the free energy tractable. The price we pay for this approximation is that we are no longer optimizing the free energy, and we have no guarantee that this will produce sensible answers, or even converge. It turns out, however, that the Laplace approximation has intriguing implications for the neurobiological implementation of Bayesian inference.

5 Predictive coding

The Laplace approximation can be used to derive arguably the most influential and distinctive aspect of FEP—*predictive coding*, according to which feedback pathways convey predictions, and feedforward pathways in the brain convey prediction errors (discrepancies between data and predictions). The idea of predictive coding has a long history in signal processing (Elias, 1955), and was previously proposed as a theory of redundancy reduction (efficient coding) in neural signals (Rao and Ballard, 1999). The novel contribution of Friston and colleagues (Friston et al., 2007; Friston, 2008; Friston and Kiebel, 2009) was to show how predictive coding could be derived within the framework of free energy minimization, and how it could be mapped onto the structure of biologically realistic microcircuits (Bastos et al., 2012).

Friston and colleagues started from the following assumptions:

- The internal (generative) model is hierarchically structured, such that hidden variables at higher levels generate hidden variables at lower levels.
- The approximate posterior factorizes across hidden variables and levels of internal model (i.e., the mean-field approximation).
- Each component of the factorized posterior is modeled as a Gaussian.

They then used the Laplace approximation to linearize the free energy and derive update rules for optimization based on gradient descent. They showed that this optimization scheme corresponds to a form of predictive coding.

It is important to emphasize that predictive coding is *not* a generic consequence of FEP, or even of FEP with a specific approximation family. It is derived from a combination of assumptions about the internal model (hierarchical organization), the approximation family (factorized and Gaussian), the approximation of the free energy (linearization around the mode), and the optimization scheme (gradient descent). With all of these assumptions in place, FEP does make claims

that go beyond the general Bayesian brain hypothesis, and have received ample empirical support (Aitchison and Lengyel, 2017; Murray et al., 2002; Summerfield et al., 2008; Egner et al., 2010; Kok and de Lange, 2015).

6 Active inference

Let us return now to the setting in which an agent can take actions to influence its observations. In this setting, FEP posits that the agent seeks to minimize *expected* free energy under future observations, which can be expressed as follows (Friston et al., 2015):

$$\sum_{d} Q(d|a)\mathcal{F}[Q(h|d)] = -\sum_{d} Q(d|a)\mathcal{D}[Q(h|d)||Q(h)] - \sum_{d} Q(d|a)\log P(d|a)$$
(12)

where $Q(d|a) = \sum_{h} P(d|h, a)Q(h)$ is the approximate posterior predictive distribution (we have simplified the treatment somewhat compared to (Friston et al., 2015), which offers a more elaborate treatment of sequential decision problems). Friston and colleagues refer to the minimization of expected free energy with respect to actions as *active inference*.

When the approximate posterior is exact, Q(h) = P(h|d), the first term in the expression is the negative information gain and the second term is the entropy $\mathcal{H}[P(d|a)]$ of the future observations d conditional on the action a:

$$\sum_{d} P(d|a)\mathcal{F}[P(h|d)] = -\mathcal{I}(a) + \mathcal{H}[P(d|a)].$$
(13)

If in addition observations are deterministic functions of actions, then the entropy term is 0 and minimizing expected free energy is equivalent to maximizing information gain. Thus, under certain conditions active inference is equivalent to the information gain policy studied in standard Bayesian treatments of information acquisition (Nelson, 2005). When the observations are stochastic and can be interpreted as reward outcomes (see next section), active inference instantiates a form of risk-sensitive control, since actions that reduce outcome variability will be favored (see Friston et al., 2015, for more discussion).

As in the previous sections, we can ask which aspects of this analysis are generic implications of the Bayesian brain hypothesis (with an information gain policy), and which are specific to FEP. We showed that FEP is equivalent to Bayesian information gain only under the special case of an exact posterior and deterministic observations. When the determinism constraint is relaxed, information gain and expected free energy will be substantively different.

7 Planning as inference

A number of papers on active inference make an additional conceptual move (e.g., Friston et al., 2009, 2012), reinterpreting the entropy term as a form of *extrinsic value*, contrasting it with the *epistemic value* of the information gain term. Central to this reinterpretation is the postulate that the

utility of an observation is equal to its log probability: $u(d) = \log P(d|a)$. (Note that I am conditioning on action here to emphasize that the free energy is being computed for a fixed policy.) This leads to a form of *planning as inference* (Botvinick and Toussaint, 2012), whereby minimizing free energy minimization optimizes a combination of expected utility (extrinsic value) and information gain (epistemic value).

At first glance, this seems rather odd; why should utility be proportional to probability? Undoubtedly there are high probability events that have low utility (e.g., if you are born into poverty then lacking access to basic goods may be highly probable). However, note that this is potentially just Bayesian decision theory in disguise: as long as I'm allowed to choose probabilities that are proportional to utilities, FEP will coincide with Bayesian decision theory. The critical step in this logic is the assumption that evolution has equipped us with the belief that low utility states are low probability, due to the fact that if our ancestors spent a lot of time in those states they would be less likely to reproduce. Whether or not this is a reasonable assumption, the technical point is that planning as inference can be understood as a notational variant of Bayesian decision theory, provided the utilities and probabilities coincide. FEP can make distinctive predictions when they don't coincide.

8 Conclusions

There are several take-home messages from this article:

- For passive observations (no actions), the predictions of FEP are indistinguishable from the predictions of the Bayesian brain hypothesis when the variational family is unrestricted (i.e., the when the exact posterior is in the variational family, and hence minimizing free energy is equivalent to exact inference).
- Predictive coding is not a generic consequence of FEP; it arises only under certain restrictions of the variational family and a specific choice of optimization scheme.
- In the active setting (observations can be influenced by actions), active inference is equivalent to an information gain policy when the approximate posterior is exact and the observations are deterministic functions of actions. When observations are stochastic, active inference induces a form of risk-aversion not found in the information gain policy.
- When utilities are interpreted as probabilities, FEP corresponds to a form of planning as inference, a class of algorithms for utility maximization. The predictions of FEP are distinguished from utility maximization when the utilities don't correspond exactly to probabilities. While FEP places value on information gain, this also arises naturally in Bayesian decision theory applied to sequential decision problems and hence is not a distinctive prediction.

These points have been made by FEP theorists themselves, but they are often somewhat obscure or buried in mathematical derivations. I have striven to make them clearer and more explicit.

The broader point of this article is that a unifying theory like FEP needs to be deconstructed in order to be properly evaluated and compared to alternative theories. By undertaking part of this deconstruction, we hope to make the elegant synthesis offered by FEP more accessible to the broader neuroscience community.

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References

- Aitchison, L. and Lengyel, M. (2017). With or without you: predictive coding and Bayesian inference in the brain. *Current Opinion in Neurobiology*, 46:219–227.
- Bastos, A. M., Usrey, W. M., Adams, R. A., Mangun, G. R., Fries, P., and Friston, K. J. (2012). Canonical microcircuits for predictive coding. *Neuron*, 76:695–711.
- Blei, D. M., Kucukelbir, A., and McAuliffe, J. D. (2017). Variational inference: A review for statisticians. *Journal of the American Statistical Association*, 112:859–877.
- Bogacz, R. (2017). A tutorial on the free-energy framework for modelling perception and learning. *Journal of Mathematical Psychology*, 76:198–211.
- Botvinick, M. and Toussaint, M. (2012). Planning as inference. *Trends in Cognitive Sciences*, 16:485–488.
- Cover, T. M. and Thomas, J. A. (1991). Elements of Information Theory. John Wiley & Sons.
- Daw, N. D., Courville, A. C., and Dayan, P. (2008). Semi-rational models of conditioning: The case of trial order. pages 431–452.
- Dayan, P. and Daw, N. D. (2008). Decision theory, reinforcement learning, and the brain. *Cognitive, Affective, & Behavioral Neuroscience,* 8:429–453.
- Doya, K., Ishii, S., Pouget, A., and Rao, R. P. (2007). *Bayesian Brain: Probabilistic Approaches to Neural Coding*. MIT Press.
- Egner, T., Monti, J. M., and Summerfield, C. (2010). Expectation and surprise determine neural population responses in the ventral visual stream. *Journal of Neuroscience*, 30:16601–16608.
- Elias, P. (1955). Predictive coding-i. IRE Transactions on Information Theory, 1:16-24.
- Friston, K. (2008). Hierarchical models in the brain. PLoS Computational Biology, 4:e1000211.

- Friston, K. (2010). The free-energy principle: a unified brain theory? *Nature Reviews Neuroscience*, 11:127.
- Friston, K. and Kiebel, S. (2009). Predictive coding under the free-energy principle. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 364:1211–1221.
- Friston, K., Mattout, J., Trujillo-Barreto, N., Ashburner, J., and Penny, W. (2007). Variational free energy and the Laplace approximation. *Neuroimage*, 34:220–234.
- Friston, K., Rigoli, F., Ognibene, D., Mathys, C., Fitzgerald, T., and Pezzulo, G. (2015). Active inference and epistemic value. *Cognitive Neuroscience*, 6:187–214.
- Friston, K., Samothrakis, S., and Montague, R. (2012). Active inference and agency: optimal control without cost functions. *Biological Cybernetics*, 106:523–541.
- Friston, K. J., Daunizeau, J., and Kiebel, S. J. (2009). Reinforcement learning or active inference? *PloS one*, 4:e6421.
- Gershman, S. J., Hoffman, M. D., and Blei, D. M. (2012). Nonparametric variational inference. In *Proceedings of the 29th International Conference on International Conference on Machine Learning*, pages 235–242. Omnipress.
- Girshick, A. R., Landy, M. S., and Simoncelli, E. P. (2011). Cardinal rules: visual orientation perception reflects knowledge of environmental statistics. *Nature Neuroscience*, 14:926.
- Itti, L. and Baldi, P. (2009). Bayesian surprise attracts human attention. *Vision Research*, 49:1295–1306.
- Knill, D. C. and Pouget, A. (2004). The bayesian brain: the role of uncertainty in neural coding and computation. *TRENDS in Neurosciences*, 27:712–719.
- Kok, P. and de Lange, F. P. (2015). Predictive coding in sensory cortex. In *An Introduction to Modelbased Cognitive Neuroscience*, pages 221–244. Springer.
- Lee, T. S. and Mumford, D. (2003). Hierarchical Bayesian inference in the visual cortex. *JOSA A*, 20:1434–1448.
- Murray, S. O., Kersten, D., Olshausen, B. A., Schrater, P., and Woods, D. L. (2002). Shape perception reduces activity in human primary visual cortex. *Proceedings of the National Academy of Sciences*, 99:15164–15169.
- Nelson, J. D. (2005). Finding useful questions: on Bayesian diagnosticity, probability, impact, and information gain. *Psychological Review*, 112:979–999.
- Oaksford, M. and Chater, N. (1994). A rational analysis of the selection task as optimal data selection. *Psychological Review*, 101:608–631.
- Rahnev, D. and Denison, R. N. (2018). Suboptimality in perceptual decision making. *Behavioral and Brain Sciences*, pages 1–107.
- Rao, R. P. and Ballard, D. H. (1999). Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. *Nature Neuroscience*, 2:79.

- Sanborn, A. N. and Silva, R. (2013). Constraining bridges between levels of analysis: A computational justification for locally bayesian learning. *Journal of Mathematical Psychology*, 57:94–106.
- Settles, B. (2012). Active learning. *Synthesis Lectures on Artificial Intelligence and Machine Learning*, 6:1–114.
- Soltani, A., Khorsand, P., Guo, C., Farashahi, S., and Liu, J. (2016). Neural substrates of cognitive biases during probabilistic inference. *Nature Communications*, 7:11393.
- Summerfield, C., Trittschuh, E. H., Monti, J. M., Mesulam, M.-M., and Egner, T. (2008). Neural repetition suppression reflects fulfilled perceptual expectations. *Nature Neuroscience*, 11:1004.
- Tsividis, P., Gershman, S., Tenenbaum, J., and Schulz, L. (2014). Information selection in noisy environments with large action spaces. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 36.