On the many ways a model can be unrealistic – and still useful

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Abstract

This essay makes the following main points:

- Making statements on the 'realisticness' of a model requires to relate a model with reality.
- Since there are many different ways to relate a model with reality, classifying a model to be 'unrealistic' requires one to specify in which sense it is unrealistic.
- Making statements about the 'usefulness' of models requires one to specify the purpose of a model.
- Since there are many different purposes for models, models can be useful in many ways.
- The purpose of a model dictates the way we assess its relation to reality; thus, a model that counts as unrealistic in one dimension, can still be useful for various purposes.
- Even models that are unrealistic in every sense can be useful: they can be directly useful by serving as well-verified parts of more complex and realistic models and they can be indirectly useful by providing inspiration and causal mechanism schemes for more complex and realistic models.
- For such 'highly unrealistic' models to be useful, they should have the properties of modularity, transparency, and generative sufficiency.

1 Introduction

In this essay I will will discuss the epistemological problem of 'unrealistic models' from an applied perspective. In practice, to decide whether a model counts as 'unrealistic' requires one to relate the model with 'reality' (I will discuss the need for a link between the model and reality below). Because there are several ways of relating models with reality, there are several senses in which models may count as 'unrealistic'.

Which way of relating a model to reality is most adequate depends on the purpose of the model. Because models may serve very different purposes (Mäki, 2009b), there is no 'best' way of relating a model to reality.

To answer the question of whether unrealistic models can be useful, I will therefore need to take two steps: First, I need to clarify the ways a model can be related to reality. This will be done in section 2. In this section I will also discuss to what extent models are (or should be) related to reality at all. Second, I need to list some common purposes of modeling and clarify how the purpose of a model determines the adequate way to relate it to reality. Section 3 will deal with this issue. Finally, in section 4 I will discuss how models that are unrealistic in every sense discussed before can still be considered useful.

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2 Relating models to reality

This essay is written from an applied perspective. Therefore, I start from the idea that models are used to represent reality. Such a view of models, although widely accepted in the literature (e.g. Sugden (2009), Mäki (2009a) or Cartwright (2010)), has recently been criticized for not accounting for established modeling practices in economics (Grüne Yanoff, 2008, 2011; Ylikoski & Aydinonat, 2014). The basic argument of these authors is that models can have epistemic value even if they are not built as a representation of reality. Their arguments have merit (and will be taken up in section 4), yet I will justify my focus on models seeking to represent reality using a theoretical and an empirical argument.

On the theoretical level, I believe that some representational aspect of models must always be involved if a model (or a set of models) is to be classified as either realistic or unrealistic. Even if one considers a model to be only a narrative or a fable that strengthens our understanding of reality indirectly, classifying the model as either realistic or unrealistic requires an assessment of the link between the artificial elements in the models with objects in reality. There is, however, at least one relation to the literature on purely theoretical models. Ylikoski and Aydinonat (2014) argue that models without a direct link to reality have epistemic value because they enlarge our *menu of possible explanations*. This menu consists of how-possible explanations (or *causal mechanism schemes*) which may serve as the building blocks for applied models. To choose some of the how-possible explanations from the menu, we must check whether they fit the situation we are currently interested in. To make this choice, we need to relate them to the real situation of interest. Thus, whenever we are interested in understanding a concrete situation (or a set of situation which share common characteristics) we need to relate our model (and its building blocks) to reality.

On the empirical level we observe that the majority of economics models today are explicit about their relation to reality. Although the 'top journals' are certainly not representative for the whole discipline, a look at the most prestigious generalist journals might be illustrative. Hamermesh (2013) found that in 2011 less than 20 per cent of the articles published in the *American Economic Review*, the *Journal of Political Economy*, and the *Quarterly Journal of Economics* were purely theoretical (in 1963, more than 50 per cent of the articles were purely theoretical). Looking at prestigious awards in economics gives a similar picture: analyzing the list of John Bates Clark medal winners, Backhouse and Cherrier (2014) conclude that economics has been becoming more and more applied and that applied work now has a much higher status in relation to pure theory than it was previously the case. Dani Rodrik summarizes this impression by stating that "these days, it is virtually impossible to publish in top journals without including some serious empirical analysis" (Rodrik, 2016).[1]

Given these two arguments I believe that focusing on models that that are (or have been) related to reality is a useful endeavor. For such models, the model-world relationship may be visualized as in figure 1.

There is a real system under investigation (SUI; often also called 'target system') that one perceives in a particular way.[2] Then one builds a model that will be used to generate knowledge about the system

[1]What such a view probably understates is the strong influence of theoretical models on empirical work. A recent example is a study for the European Commission where the authors investigated empirically the impact of product piracy on sales (van der Ende et al., 2017). The stylized neoclassical models they rely on predict that strong property rights preventing product piracy increase sales. This prediction is true only for the case of movies. In all other sectors there was no effect, in the case of video games piracy *increased* sales. In a related academic publication using the same data, however, Herz and Kiljanski (2016) only consider the empirical evidence for the case of movies. My read of this is that they consider only the part of the empirical investigation that fits their theoretical model, thus the impact of the 'empirical revolution' in economics can surely be debated.

[2]Even this process of perception could be thought of as a first step in building a *mental model* (Forrester, 1971; Johnson-

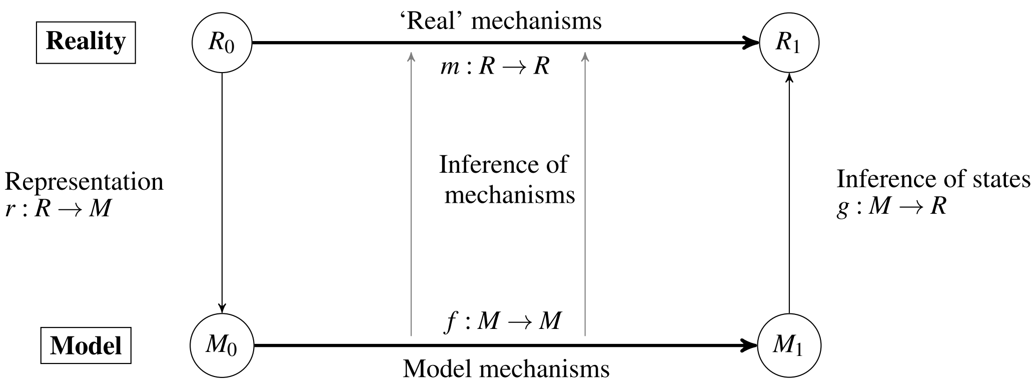


Figure 1: The applied modeling process.

under investigation. This model can be a verbal, equation-based, algorithmic, symbolical or any other representation of reality. In any case, the representation of reality is less complex than reality itself – otherwise building the model would have been useless (see already Robinson (1979)). Thus, we can think of the process of representing reality in a model as a (many-to-one) mapping process from reality to the model world. This mapping process r takes as an input the states of reality R and gives as an output the states of a model M.

Then we explore the behavior of our model, i.e. we construct and study its mechanisms, which can be thought of as a mapping f from one state of the model to another. A large part of economists does so by computing an equilibrium state of the model and by deriving its implications for the other state variables of the model. This way, the model exploration process often takes the form of a rigorous mathematical proof.

But there are other ways to explore the behavior of one's model, e.g. through a numerical simulation or through a *Gedankenexperiment*. The activity of exploring the model and ensuring that the models does what it is supposed to do is not concerned with the real world, only with the model world. In the applied literature, this activity is usually called *model verification* (see figure 2a).

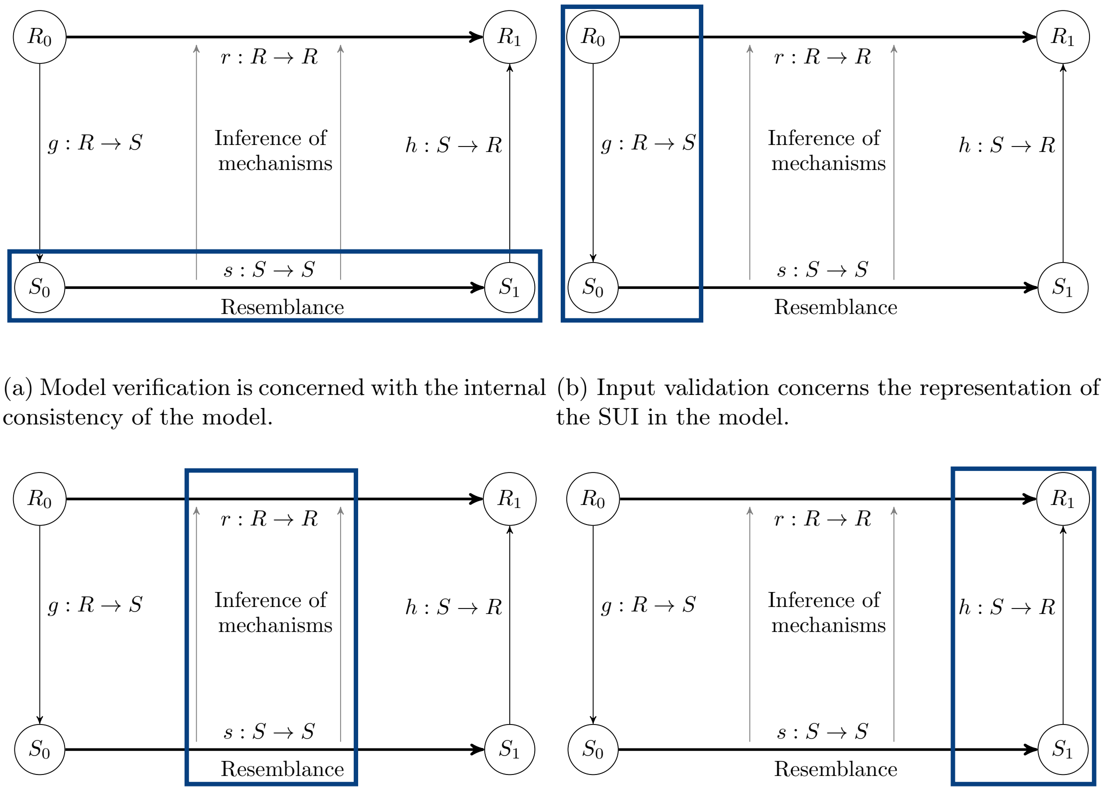
After having verified a model, one may relate it to reality. In the applied literature this is called *model validation* and we can distinguish (at least) four different approaches to do so (Tesfatsion, 2017):

1. Input validation
2. Process validation
3. Descriptive output validation
4. Predictive output validation

These different forms – of which the boundaries are fluid in practice – are compared visually in figure 2.

Input validation is illustrated in figure 2b and assesses the ability of the model at $t = 0$ to represent certain aspects of the system under investigation. In a model of a financial market, for example, input validation asks whether the number of traders in the real market and the model or their initial wealth distribution is similar.

Laird, 2005), a necessary step predating the conscious model building process.



(a) Model verification is concerned with the internal consistency of the model.

(b) Input validation concerns the representation of the SUI in the model.

(c) Process validation assesses the resemblance of real-world mechanisms in the model.

(d) Output validation addresses the fit of the model or its ability predict future states of the SUI.

Figure 2: Illustrations of model verification and the different forms of model validation.

Process validation is illustrated in figure 2b and assesses the credibility of the mechanisms in the model. Because mechanisms are not directly observable, no model will ever be fully process-validated. But there are many reasonable ways to assess the question of whether the implemented mechanism A is more or less likely to operate in the real world than mechanism B. These ways include expert and stakeholder validation (or 'participatory validation', Smajgl and Bohensky (2013)), process tracing (Steel, 2008, ch. 9), face validation (Klügl, 2008) and a clever use of experiments (e.g. Bravo, Squazzoni, and Takács (2015)).[3]

Descriptive output validation is illustrated in figure 2d and assesses the extent the output of the model can replicate existing data, or whether the story of the model matches our perception of what is going on in reality. Or, to speak with figure 1, we compare the states M_i with R_i for all $i > 0$. For example, if we have built a model for the UK economy, we may compare the time series for GDP from the model with real-world data on the GDP of the UK.[4] I imagine this form of validation is closest to what Grüne Yanoff (2008) and Sugden (2009) refer to when assessing the credibility of a model.[5]

[3]While process validation is hard, the merits of models that explain via the provision of mechanism gets more and more acknowledged and the validation of models in terms of mechanisms becomes more and more a *desideratum* (Steel, 2004; Deaton, 2010; Reiss, 2011; Grüne Yanoff, 2015).

[4]Although descriptive output validation is maybe the most commonly used form of validation (at least in economics), a sole focus on this kind of validation is highly problematic for a number of reasons such as *empirical risk minimization*, *overfitting* or *equifinality*. See Gräbner (2017) for more technical details.

[5]The notion is somehow different as Grüne Yanoff (2008) refers to general and purely theoretical models and compares them to novels. When applied to a concrete situations, the adequacy of the assumptions must be scrutinized more rigorously.

Purpose	Verification	Input val.	Process val.	Desc. val.	Pred. val
Provide predictions	★	★			★★★
Explain what happened	★★★	★★	★★	★★★	
Scenario analysis	★★★	★	★★		★★

Table 1: A possible prioritization of verification and the different types of validation, depending on the model purpose.

Predictive output validation is also illustrated in figure 2d. Yet it differs from descriptive output validation: here one really assesses the predictive capacities of the model and not its ability to replicate existing time series. Therefore, this kind of validation usually requires a formal model and a lot of good quantitative data. Practically, the existing data is separated into a test set and a training set. The model is fitted to (or 'trained on') the training set. Then one assesses its ability to predict the test set. This avoids the problem of over-fitting and empirical risk minimization.

These four approaches to model validation echo the various ways a model can be related to reality: all of them assess the realisticness of the model in a different way. Based on these validation criteria, it is reasonable to call a model 'realistic' if it scores well with respect to a particular form of validation. For example, a model is called realistic in the sense of its descriptive output capacity whenever it can be calibrated well to existing observations. Of course, the same model may score very differently in the various forms (and may not even be accessible to all of them). In fact, modelers usually face trade-offs in terms of model design: making a model easily amendable to one kind of verification/validation makes it more cumbersome to validate/verify with another kind (see Gräbner (2017) for more details). Thus, it is important to be precise in what sense we consider a model to be 'realistic' or 'unrealistic'.

3 The purpose of a model, and its link to reality

Models serve different purposes (Mäki, 2009b). The EU commission uses models to predict the potential output of EU member states such that it can set interest rates accordingly. Public economists use models to investigate why the members of one firm invest more into their private pension plans, and whether these mechanisms can be put into effect in other firms as well. Companies use models because they want to identify possible scenarios for future market development such that they can prepare adequate reactions. There are many more reasons why one builds models (see e.g. Epstein (2008) for an overview).

The important message here is this: the purpose of a model dictates the way we assess its relation to reality. If a state agency is only interested in how fast county X will grow next year, the model should be validated through predictive output validation. From this perspective, a model is realistic if and only if it provides good predictions.

For scholars who are interested in designing policies that stimulate investments into pension plans, such models are less useful. Models that score high in terms of predictive output validation often involve complex machine learning algorithms. They do not necessarily tell us anything about why something will happen in the future. This is not useful if we want to design policies (Grüne Yanoff, 2015). Instead, models used for such purpose must be process and input validated. Accordingly, the same model that may count as 'realistic' in the previous example, might now count as highly 'unrealistic'.

Table 1 provides an exemplary and rough prioritization of validation procedures depending on the purpose of the model. The ranking can surely be debated. The important point I want to make is that the way we relate a model to reality depends on the purpose of the model and that a model that scores well in one kind of validation may score poorly in another kind of validation. Consequently, whether a model counts realistic or unrealistic depends on the model purpose.

From this viewpoint it is clear that a model that is unrealistic in one sense can still be useful for certain purposes. The question is: what about models that score poorly in all four validation techniques simultaneously? Can they still be useful for applied work?[6]

4 What to make of highly unrealistic models?

4.1 How highly unrealistic models can be useful

I call models that score poorly in all four validation dimensions simultaneously *highly unrealistic models*. These models can be useful in a direct or an indirect way:

1. They can be useful in a direct way by serving as building blocks for more complex and more realistic models (Gräbner et al., 2017).
2. They can be useful in an indirect way by serving as an inspiration for more complex models and by extending the menu of possible explanations via well-understood causal mechanism schemes (Ylikoski & Aydinonat, 2014).

A common drawback of complex models is that they are difficult to verify and that it is not easy to understand their internal dynamics. Building models from well-understood "model skeletons" can help to (partly) remedy this problem: as we have illustrated in Gräbner et al. (2017), it is useful to start with a very stylized and abstract model, which is easy to understand. Ylikoski and Aydinonat (2014) would even start from well-understood causal mechanism schemes. Then, one may build a more complex model that contains the simpler model as a special case, but extends it such that it can be more realistic. By 'docking' the two models, i.e. to simulate the simpler model via the more complex one, one can engage in 'sequential modeling', i.e. the construction of a series of models, in which later models include the previous ones as special cases, and generalize their results. This endeavor is attractive, since models that are easier to validate are often more difficult to verify, and by aligning models sequentially, the respective strengths of (well verified) 'unrealistic' and (well validated) 'realistic' models can be combined: in sequential modeling, the property of good verification 'bleeds over' from the simple to the more complex models.

But highly unrealistic models can also be useful in an indirect way. This argument draws upon the literature on theoretical models, i.e. models that were built without an aspired relation to reality (Grüne Yanoff, 2008; Ylikoski & Aydinonat, 2014). Ylikoski and Aydinonat (2014) argue that such theoretical models extend the menu of possible explanations through well-understood causal mechanism schemes. This way, these models may serve as an inspiration to build more complex models: if I look at a particular economic system, and I want to understand this system well I need to build an explicit model. But building a model does not happen out of the blue. Good models develop like good technologies: they exploit and extend the ideas of previous research. A highly unrealistic model can inspire model builders by giving the intellectual puzzle pieces they need to build the adequate model. To use a common example, Schelling's checkerboard model is helpful for building applied models of urban economics because it contains ideas about how individualistic decisions can lead to unintended consequences on the systemic level. People who seek to build realistic models will still benefit from the ideas presented in the Schelling model because it reminds them to be mindful and explicit about how individual actions aggregate in their model.

[6] That they can be useful for theoretical work has been argued convincingly by e.g. Grüne Yanoff (2008) or Ylikoski and Aydinonat (2014).

4.2 Demands for "Good Unrealistic Models"

However, to be useful in the senses just outlined, models should meet some demands:

- **Modularity**: the parts of the model should be controllable in the sense that they can be activated or deactivated such that it is clear what consequences the different parts of the model have on the overall model results.[7] Also, the model should be built in a way that when it is used as a building block for a more complex model, it should be possible to activate or deactivate the mechanisms of the model, such that it is clear what its causal impact on the results of the more complex model really is. This is usually easier for computational than for verbal of equation-based models.

- **Generative sufficiency**: the model should clearly imply a mechanism that derives the outcome of the model from its initial conditions; also, the pathway from the initial to the final state of the model should be clear and explicit (Epstein, 2007; Ylikoski & Aydinonat, 2014).[8]

- **Transparency with regard to their verification**: the mechanisms that drive the dynamics of the model, or that allow the derivation of the conclusions from the assumptions should be clearly described and reproducible. The best way of model verification is a mathematical proof that derives the conclusions stepwise from the assumptions. Yet a proof is not always feasible, either because the model is not tractable or because it is not formal. In these cases the logic of the model must be clearly described, and, if the model is formal, extensive sensitivity studies must prove the robustness of the model results.

Note that all these demands are easier to meet for simple models than for complex models. This is no coincidence: in practice, modelers often face trade-offs in the design of models that prevent a model to do well in terms of verification and all four validation categories. If we change our model such that it performs better in one dimension (e.g. input validation), it usually performs worse in another dimension (e.g. verification or predictive output validation).[9] Therefore, relating highly unrealistic models that are easy to verify to more realistic models is a powerful way of expanding our scientific knowledge. This way is not accessible for anyone who abstains from the construction and use of highly unrealistic models.

5 Summary and conclusion

In this essay I have discussed the usefulness of unrealistic models from an applied perspective. I argued that to classify a model as either realistic or unrealistic we need to relate the model to reality. There are at least four different ways of doing so. Since a model can count as realistic in one sense and unrealistic in another, one has to be very specific in which sense a model is considered (un)realistic. Which way of relating a model to reality is most adequate depends on the purpose of the model. Hence, models that are unrealistic in one sense can still be useful for particular purposes.

Even models that are unrealistic in all dimensions discussed in this essay can be useful if they meet the criteria of *modularity* and *generative sufficiency* and if they are *transparent* and *well-verified*. Such "good unrealistic" models can be useful directly by representing potential building blocks for realistic

[7]For example, assume a model in which agents need to make certain decisions. A modular model structure implies that it is possible to activate or deactivate the part of the model that is responsible for the agents to make mistakes. This way it would be easy to compare the output of the model when agents do make mistakes with the output in which the agents do not make mistakes. Consequently, the causal implications of mistakes are easy to identify. This is harder if the module that controls the mistakes of the agents also controls other aspects of the model, e.g. the speed with which agents make decisions. This would make, it harder to isolate the effects of the respective mechanisms.

[8]Many equilibrium models do not satisfy this condition because they are only concerned with the existence of certain equilibria, but not with the particular pathway through which the equilbria can be reached from arbitrary initial conditions.

[9]See Gräbner (2017) for a more complete comparison between verification and the different validation forms, and technical justifications.

models (Gräbner et al., 2017), or indirectly by serving as an inspiration for more complex models and by extending the menu of possible explanation via well-understood causal mechanism schemes (Ylikoski & Aydinonat, 2014).

If highly unrealistic models satisfy these demands, they can be useful even if considered from an applied perspective.

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