Simplicity and Simplification in Astrophysical Modeling

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With the ever-growing quality of observational data in astronomy, the complexity of astrophysical models has been increasing in turn. This trend raises the question: Are there still reasons to prefer simpler models if the final goal is an actual model-target comparison? I argue for two aspects in which astrophysical research may favor models having reduced complexity: first, to address the problem of determining the values of adjustable parameters and, second, to pave the way for a validation of the model based on the modeler's understanding of the scope of the model and the critical processes on the target's side.

1. Introduction. Numerical modeling plays a central role in astrophysical research. Given the vast and apparently irreducible complexity of astrophysical phenomena, together with the enormous temporal and spatial scales involved, numerical models and simulations have become indispensable tools for the interpretation of astrophysical observations, in particular, and the theoretical understanding of astrophysical processes, in general (see Anderl [2016] and references therein). By its very nature, the astrophysical analysis of astronomical observations consists of the application of physical theories to cosmic phenomena, using models and simulations.

The details of this procedure rely very much on the nature of the astronomical data at hand and in particular on their angular resolution. The angular resolution describes the ability of a telescope to spatially distinguish details in the observed region—a model will have to reproduce this degree of detail in a model-target comparison. Historically, this dependence of the required

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"granularity" of the astrophysical model on the quality of the astronomical data has led to a tendency for the complexity of astrophysical target-directed models to increase over time in parallel with progress in observational technology.

One reason is that unresolved observations justify extensive geometric symmetry assumptions: the smearing influence of the telescope beam makes things appear smoother than they really are. For instance, cosmic phenomena appear circularly symmetric if the circular beam is larger than the scales of the underlying asymmetries and inhomogeneities. Even if the input physics and geometry are highly idealized compared to what is expected, the agreement between the model and low-quality data can still be very good in such cases. With ever-improving telescope technology and ever-increasing data quality however, previously satisfactory models often have proven to be insufficient by the standards of new incoming data. Accordingly, modelers are obliged to improve their models by including additional processes or by reducing the level of simplifying assumptions, approximations, and idealizations if they still want to achieve a good fit between constraining observations and the model.

These developments, induced by progress in observational and computing technologies, are mirrored in changing "representational ideals" (see Weisberg 2013) that govern the building process and the use of these models. Forty years ago, probably motivated by a lack of both numerical computing power and high spatial resolution data, many models in astrophysics were intentionally simple, aiming at a general theoretical understanding of cosmic processes in terms of their core causal factors, rather than attempting to provide a successful reproduction of a particular set of observations. Models should be as simple as possible (but no simpler) in order to facilitate a scientist's understanding of what is going on. Today, most astrophysical models have become much more complex than those early models, many of them now following the representational ideal of "completeness" (Weisberg 2013): the more details relevant to the properties of the target phenomenon included and hence the better the fit to the data, the better the model. The ideal demands the addition of more features, more complexity, and more precision to the model whenever possible.

The overall goal of astrophysical research, however, has not changed over the last decades: the interplay of models and observations should facilitate an understanding of what is going on in the cosmos. But, in the interim, has the ideal of simplicity become irrelevant or dispensable in modern, data-driven astrophysics? If not, what then is the role of models that do not aspire to the representational ideal of completeness in the interpretation of astronomical data? This article aims at addressing these questions by studying the example of shock models featuring different degrees of complexity, which are applied in the interpretation of high spatial resolution, galactic data.

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Accordingly, this example is based on observations that contain a high level of information on the physics happening in the observed cosmic region, which may become available to a similar degree for extragalactic targets only with future generations of interferometers. In this respect the example is chosen as an extreme case of a situation with very strong observational constraints that may particularly favor the representational ideal of completeness.

Using this example, I put forward two reasons for which simple models are of value for the interpretation of astronomical observations: first, to address the problem of determining the values of adjustable model parameters by systematically exploring the full parameter space and, second, to allow for an internal validation of the model, as part of an assessment of its structural uncertainty. In the context of the latter, we find appeals to the rather unclear notion of "physical intuition," which can be analyzed, I claim, as a sort of understanding containing both elements of explicit knowledge and practical know-how. It is the acquisition of this kind of understanding where simple models play a crucial role, being objects of active experimental exploration.

The article is structured as follows: section 2 will briefly lay out the epistemic role that numerical models play in the explanation of individual cosmic phenomena. Then, three different astrophysical models will be introduced that individually describe the phenomenon of interstellar shock waves, comprising increasing levels of mathematical and physical complexity. Using this example, section 3 will discuss the step of model instantiation necessary for a target-model comparison based on astronomical observations and will show how simple models have an advantage in this regard. Section 4 considers how the structural uncertainties of the model can be assessed in such a comparison, again highlighting an advantage of simpler models. To help show how this advantage arises, it is suggested that the notion of "physical intuition," often put forward in this context, can be analyzed as a kind of understanding. Finally, section 5 presents the main conclusions of the article.

2. Explaining Cosmic Phenomena: Interstellar Shocks. In astrophysics, the explanatory power of models is often used to gain an understanding of spatiotemporally located cosmic phenomena in terms of their individual histories and their environmental conditions. Typical questions in this context would be, Why is the Class 0 protostar IRAS4B surrounded by a ring of N_2H^+ emission (Anderl et al. 2016)? Or, What happened when the supernova remnant W44 ran into a nearby molecular cloud (e.g., Anderl, Gusdorf, and Güsten 2014)? Such studies resemble similar problems in the historical sciences, where traces of some past incidents are interpreted in terms of a unifying causal history (e.g., Cleland 2002). The Sherlock Holmes methodology (Anderl 2016) of these observational disciplines, like archeology, geology, or paleontology, basically follows hypothetico-deductivism: possible causal stories that can explain the observed traces are hypothesized, and subsequently

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"smoking gun observations" are identified and searched for that will be able to rule out some of the competing explanations.

In this methodological picture, numerical models are used to reproduce observations of a specific target, based on a hypothesized astrophysical scenario. They will also make predictions for further observations that may support or refute the suggested scenario. Accordingly, and as already mentioned above, the available data determine to some degree the required granularity of the model predictions (i.e., their spatial and spectral resolution and the required predicted features of the respective cosmic information carrier, like wavelength and polarization in the case of electromagnetic radiation). If the model predictions are too detailed, model selection is underdetermined by the available data; if the model predictions are too coarse, then they will not be able to serve as "smoking gun" predictions. However, even within these general constraints, a spectrum of models constructed at varying levels of complexity is still possible and actually in use.

The target phenomenon of the modeling case study I will discuss is an interstellar shock wave. A shock wave is a pressure disturbance that moves at velocities exceeding the local sound velocity of the surrounding medium. In such a situation, the upstream medium cannot dynamically anticipate the disturbance before it arrives. Then the medium is suddenly compressed, heated, and accelerated within a thin shock front. In the universe, shock waves are a ubiquitous phenomenon occurring on many different scales and in many different contexts—from jets and outflows generated by newborn stars, to violent supernova explosions (see, e.g., Draine and McKee 1993). The shock-heated gas often cools radiatively in a characteristic way; a fact that makes shocks important observational tracers of the underlying dynamical processes and raises the need for theoretical tools that help to analyze this shock radiation.

In the simplest situation of nonradiative, fast shocks in tenuous media, it suffices to describe the jump in the fluid variables (the fluid density, pressure, velocity, and temperature) that occurs across the shock front. In denser, molecular media where magnetic fields play a crucial role in the fluid dynamics, a description of the fluid chemistry, as well as of the magneto-hydrodynamics (MHD), is indispensable. Because of the complexity of this problem, the description is usually done with far-reaching symmetry assumptions, which may be partly removed for a more realistic description of particular shock situations. Roughly in terms of increasing complexity, three different modeling approaches can be distinguished.

The Rankine-Hugoniot relations constitute the simplest possible shock model, described by the following set of equations:

$$\rho_1 u_s = \rho_2 u_2 \tag{1}$$

$$\rho_1 u_s^2 + p_1 = \rho_2 u_2^2 + p_2 \tag{2}$$

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$$e_2 - e_1 = p_1 u_s - p_2 u_2, \tag{3}$$

where u_s is the shock velocity, ρ_1, p_1, and e_1 are preshock density, pressure, and energy of the gas, respectively, while subscript "2" identifies postshock values of these fluid variables. These equations are derived from conservation principles across the shock front together with some (usually justifiable) assumptions about the physics within (for a derivation see, e.g., Landau Lifshitz 1959; Tielens 2005). They relate the properties of the preshock medium to the properties of the medium right behind the shock front. The description is one-dimensional and ignores chemistry and radiative transfer. The set of equations is simple enough to offer analytic solutions for a few prototypical problems (e.g., adiabatic shocks and isothermal shocks).

The Paris-Durham shock code (Flower and Pineau des Forêts 2003) is a computer model that calculates the MHD dynamics, in parallel with the shock chemistry and shock radiation, across a shock that has reached a stationary state. Accordingly, it includes the description of many microphysical processes in addition to the calculation of the basic fluid variables for the neutral and the charged fluid components. The heart of the computation is a set of more than 150 coupled differential equations. The price to pay in order to reach this high level of microphysical detail within moderate computation times (order of minutes) is to restrict the geometry to plane-parallel and thus one-dimensional shocks that move perpendicular to the direction of the magnetic field.

The pseudo-3D bow shock model (Gustafsson et al. 2010) lifts the geometrical shortcomings of the Paris-Durham model by sticking stationary one-dimensional models onto a three-dimensional (3D) bow shock surface. Using this pseudo-3D approach instead of a full 3D integration, it can still keep the high level of details in the chemical and radiative transfer description at a reasonable computational cost (order of hours).

As described before, I focus here on the modeling of individual cosmic phenomena in terms of their specific history and environmental conditions. The property of the shock that is observationally accessible is its electromagnetic radiation. For a meaningful fit between the model and the target, the model should ideally include all crucial processes and features of the shock that are causally linked to the generation of this radiation. This requirement already excludes the "bare" Ranking-Hugoniot equations from a direct target-model comparison in most cases because their structure is too simple to make predictions on particular shock intensities. Given the representational ideal of completeness, it seems that the 3D bow shock model should naturally be best suited for the modeling of actual observations, given its higher geometric complexity than the Paris-Durham model. It is, however, worthwhile to look at the actual process of target-model comparison in more de-

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tail. This process can be understood as a two-step procedure: model instantiation and assessment of model uncertainties.

3. The Value of Simplicity 1: Model Instantiation. The Paris-Durham and the bow shock model both constitute families of models generated by a number of free model parameters. These parameters belong to one of two classes: some of the parameters describe intrinsic properties of the shock itself, like its velocity or its orientation. The remaining parameters describe specific environmental conditions like the preshock density or the magnetic field. In the application of the shock model to the observations, determining these free parameters is the first problem the modeler has to face. The underlying question of this "model instantiation" (Orzack and Sober 1993) is "What is the best-fitting individual model within the whole family of models?"

A direct determination of free model parameters in astrophysics is rather involved because their values usually need to be derived theoretically, if at all possible, from their impact on the observed information carriers such as the emitted electromagnetic radiation. In addition, the projection effect of 3D structures onto the two-dimensional celestial sphere complicates the situation substantially.

The Paris-Durham model has three free parameters, which need to be externally fixed (the shock velocity, the preshock density of the medium that the shock wave is running into, and the magnetic field strength in the preshock medium). For all these unspecified parameters it is possible to get observational constraints on their probable values. Given such constraints and the relatively short computing time of the model, a reasonable approach to model instantiation is to compute a grid of shock models within the estimated parameter boundaries and then determine the best-fitting model in comparison with the observations using, for instance, a χ^2 minimization method (see, e.g., Anderl et al. 2014).

The situation is more complicated in the case of the 3D bow shock model. Here, five additional, observationally poorly constrained parameters that describe the direction of the magnetic field and the shape and orientation of the bow shock surface need to be fixed. Furthermore, the grid-based approach as described above is not practical for this model family because of the higher dimensionality of the parameter space needed to be covered and the much higher computation time required per model. Accordingly, the search for the optimal set of parameter values is typically done manually and with incomplete sampling (Gustafsson et al. 2010), which significantly hampers the search for the best-fitting model.

So here we see one advantage for simpler models that have a small number of unspecified parameters, namely, that the model instantiation step can then employ a systematic search of parameter space to identify the best-fitting models, whereas this is often not possible for more complex models. This might

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seem as only a minor advantage, insofar as it only comes into play when simple models are still complex enough to provide some understanding of the target system. In these cases, however, a crucial point is that a systematic search of the parameter space can uncover degeneracies: multiple solutions in unconnected regions of the parameter space that correspond to fundamentally different underlying physical conditions. Such a behavior is well known in complex nonlinear systems (Strogatz 1994). A well-studied case is interstellar chemistry, where bistability creates two equally possible steady-state solutions with very different degrees of ionization (e.g., Le Bourlot et al. 1993). Another example is galaxy formation models (see, e.g., Bower et al. [2010], where a Bayesian approximation to a more complex model is used to study the full parameter space). In shocks, degeneracies with respect to certain available observations can, for example, occur between different types of shocks at different preshock densities (e.g., Anderl et al. 2014). In these cases, a systematic search of the parameter space is indispensable, as it can help one to avoid arriving at a mistaken conclusion about the underlying physical conditions; in some cases, this might be a good reason to trade off fast computability against complexity.

4. The Value of Simplicity 2: Assessing Structural Uncertainty. The next challenge the modeler has to meet is to evaluate the representational and predictive power of the model and thereby answer the question, "What can we actually learn about the real-world phenomenon from the best-fitting model and its predictions?" There are different kinds of uncertainties regarding the model predictions that are important in this context. One source of uncertainty concerns the data generation and processing yielding the data model that is finally compared with the model output. I will not discuss this uncertainty here because its analysis opens yet another field of discussion and would lead us away from our original question. The same holds for another source of uncertainty, which is numerical approximation methods. The focus will be on "structural model uncertainty" (Winsberg 2010, 100)—uncertainty associated with model predictions, which stems from the model's reliance on uncertain auxiliary assumptions and on approximations and simplifications relative to the 'full' physics. This can be a particularly significant source of uncertainty.[1]

Assessing the model's structural uncertainty is a step in the model application that is much less straightforward than parameter fitting. Questions that are to be answered in this context concern the robustness of predictions

1. Even more fundamental is the question whether the structure of the model—with some set of parameter values—is even capable of reproducing something that sufficiently resembles the underlying causal history of the phenomenon. In the case of shock models, this "structural adequacy" is usually assumed, and the focus is on understanding and quantifying the predictive uncertainty that arises from the model's approximations, simplifications, etc. Accordingly, structural uncertainty is my focus here.

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with respect to the particular nature of the model or the reliability of particular assumptions with respect to the model application. Many of these aspects are covered under the concept of "model validation," although the methodological steps of validation and verification are usually hard to separate (Winsberg 2010).

In principle, at least four different strategies can be applied in order to assess the model's structural uncertainty and to establish trust in the model and the results derived from it: (1) comparison with analytical solutions, (2) benchmarking against real-world data, (3) benchmarking against other models, and (4) internal testing/analysis of the model. A comparison with analytical solutions is a helpful tool to check subparts of the model during model development, but for complex astrophysical systems, the reason for numerical modeling is precisely the absence of simple analytical solutions. A similar problem exists regarding the benchmarking with real-world data. In most cases, it is impossible to reconstruct the complex astrophysical phenomenon in its entirety under laboratory conditions, so parallel experimenting is excluded as a possible way to probe the validity of the model. Also, the comparison with other models that incorporate different assumptions and simplifications to understand the robustness of model predictions with respect to the internal structure of the model is difficult because for a given astrophysical phenomenon there is usually not a considerable variety of different models. For instance, to describe shocks in molecular clouds, there may only be five suitable models worldwide. Furthermore, as these models usually do not implement the same set of physical processes and modeling assumptions, it is also very difficult to derive reliable conclusions from their agreement/disagreement (for an analysis of typical epistemic problems occurring in the context of ensemble studies, see, e.g., Lenhard and Winsberg 2010; Parker 2011).

Accordingly, internal model testing plays an important role in astrophysics. On the one hand, this describes a model analysis yielding thorough knowledge of properties, states, and transitions among states allowed by the model (see, e.g., Sundberg 2010). This knowledge of detailed model behavior can then be checked for internal consistency and be compared to the expected behavior of the target phenomenon. Loosely speaking, it is tested whether the behavior of the model with respect to varying initial conditions and parameter values "makes sense" with respect to the basic construction principles of the model itself and with respect to what we know about the target. On the other hand, this analysis may also go beyond the existing model in that structural ingredients of the model itself may be varied, and the implications for the resulting output (i.e., their robustness) are studied.

The feasibility and success of this strategy of internal model testing, however, depend on the internal complexity of the model. A complete and methodologically well-defined model analysis using the tools of nonlinear dynamics (e.g., Strogatz 1994) is impossible for very complex systems. At the

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same time, complex models exhibit a quality that Winsberg (2010, 93) calls "epistemological holism," meaning that the complex interplay of different parts of the model (i.e., different modeling modules) makes the model analytically impenetrable. Even if individual modules of the complex model are well tested and calibrated individually, there is no straightforward way to predict the overall interconnected performance of the model. Or looking at it the other way around, by observing the model's behavior on its own, this behavior is very hard to interpret in terms of the model's internal structure.

One concept that is regularly used by scientists when it comes to the understanding of the scope and the limitations of particular analytically impenetrable models is that of "physical intuition," which is sometimes taken to refer to the ability of a scientist to reliably estimate the performance and limitations of a model "intuitively" (Goldsmith 2015). Philosophers working on the epistemology of simulations have used terminology that seems to hint in the same direction.

Humphreys (2004) speaks about "subject-matter-dependent knowledge," which is required in "considerable amount" in order to apply a model to actual cases. More precisely, he calls the part of knowledge that concerns the model itself a "quite refined sense": "Template builders usually have a quite refined sense of which of the components that go into the construction of the template are well justified and which are not" (81).

Winsberg (2010, 16, 64) calls "physical intuition" one of three ingredients for model building apart from theoretical knowledge and a knowledge of model-building methods. These also constitute the three components of background knowledge that are necessary to sanction the trustworthiness of a model. As an example, he refers to a modeler's choice to describe some fluid using a steady-state assumption. However, he distinguishes "physical intuition" from other explicit forms of background knowledge unrelated to theoretical or methodological principles when he says: "I characterize reliability (for modeling principles) in terms of being able to produce results that fit well into the web of our previously accepted data, our observations, the results of our paper-and-pencil analyses, and our physical intuitions, and to make successful predictions or produce engineering accomplishments" (133).

Finally, Weisberg (2013, 69) describes another aspect of what scientists might call "physical intuition," which he mentions when discussing the "face-value practice of modeling." This includes the ability to fill in the model description, which is rather sparse in terms of explicit information on the respective mathematical model, with actual details. By doing this, the imagined, fictional scenario is treated like what would be a concrete scenario if it were real. According to Weisberg, this practice helps thinking about very complex models and assists in the development and refinement of the model. In the context of internal model testing, the ability to understand and imagine all the consequences of the sparse model description is often a crucial precon-

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dition in order to check the internal consistency of the model and the scope of its possible applications.

Thus, both scientists and philosophers of science alike sometimes seem to appeal to something like "physical intuition" when they characterize the practice of simulation. Exactly what such physical intuition consists in, however, remains unclear. In the remainder of this section, I offer some further remarks on how we might think of "physical intuition" (sec. 4.1), which will help with my articulation of a second advantage of simple models (sec. 4.2).

4.1. Physical Intuition as Understanding. From the above discussion, it seems like there exists something like a "physical intuition," a "refined sense," or a certain sort of "ability" that plays an important role in assessing the structural uncertainty of a model that is used in a model-target comparison. This assessment will have to deal with two different domains, the target and the model domain. Regarding the target, the relative contributions of causal factors on different temporal and spatial scales in the production of the target phenomenon need to be understood. Regarding the model, it needs to be understood whether its internal setup is suited for making useful claims about the target phenomenon. This encompasses an understanding of dependencies in the model and of its overall behavior, including the effects of possible changes to the modeled system. But what kind of understanding are we talking about here?

Parker (2014) distinguishes two different notions of understanding, which can be helpful to answer this question. The first sort is closely related to causal explanations and describes "understanding why an event/phenomenon occurs" (338). It consists of having explicit knowledge of the mechanism by which a phenomenon is produced. The second sort is described as "understanding a complex phenomenon/system" (339) and contains both knowledge and "know-how." The latter describes a practical competence of synthesizing and applying knowledge to predict the behavior of the system in different circumstances. Parker stresses that both sorts of understanding are related: An understanding of underlying mechanisms by which salient features of a phenomenon are produced contributes to the understanding of that complex phenomenon: "the first sort of understanding is typically part of the second" (340).

"Physical intuition" that seems relevant for the construction of models of complex phenomena appears to belong to the second sort of understanding. In particular, this is because it seems to embrace elements of implicit knowledge (see Polanyi 1958): it is closely related to a practical competence or ability in dealing with the complex target phenomenon and its model representation. The scientist is able to apply her knowledge of the phenomenon and the model in a way that she can make correct predictions about their respective behavior. This puts her in a position to understand both the potential limitations as well as the reliability of the model representation. This practical com-

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petence rests, however, on an understanding of the first sort—the understanding of the underlying mechanisms.

Now, if we have a closer look at how this particular competence—which seems to constitute at least one kind of "physical intuition"—is being acquired, the second important role of simple models in the process of a target-model comparison will become clear.

4.2. Understanding from Experimenting on Models. If we trace the fuzzy notion of "physical intuition" back to the understanding of a complex phenomenon or system including both knowledge and know-how (understanding of the second sort, in Parker's terminology), we can try to identify possible sources of this sort of understanding. Following Parker (2014), it seems like one source of this understanding can be experimenting on models. Experimental manipulation of the implemented physical processes, variation of the values of model parameters, or changes in the initial and boundary conditions can help the scientist to investigate the various dependencies in the model and its overall behavior. As Parker describes it, this investigation can also provide a starting point for gaining an understanding of the mechanisms underlying the real-world phenomenon.

For this task, simple, analytically penetrable models that are veridical with respect to the implemented physics but contain only the core causal factors of a certain process can be used as mediators that help to assess the behavior and relative impact of the putative causal ingredients of the target system and its model representation.[2] Parker (2014) describes how simpler models can be used to construct explanations of the behavior of more complex models, such that understanding of these complex models ultimately relies "on a hierarchy of models of increasingly complexity" (351). The underlying idea is that simple models can provide how-possibly understanding (also see Hartmann [1998] and Reutlinger, Hangleiter, and Hartmann [2017] on the epistemic goal of toy models), which will then serve as a basis both for the understanding of the complex phenomenon and for the know-how of how to build and use the complex model. This practice of experimenting on simpler models (or subparts of the complex model) constitutes an important part of model development and validation in astrophysics, even though this activity is usually rather invisible in the resulting publications.[3] In the example of shock modeling, the underlying hierarchy of models of increasing complexity is represented in the

2. In fact, it is not only the greater analytic penetrability of simple models that makes them preferred means of experimenting. Experimenting on complex models may also suffer from computational restrictions like very long computation times or numerical instabilities.

3. The methodology here shows some similarity to establishing trust in an experimental setup (Franklin 1986; Winsberg 2010, 64).

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literature describing different versions of the shock model since the 1980s. Reduced versions of the present shock code are still in use for training purposes, and the epistemic accessibility of the Paris-Durham shock code is indeed put forward by scientists as an argument against the use of the much more epistemically opaque 3D model.

To sum up, interaction with models that are analytically penetrable plays an important role in obtaining an understanding of the complex target phenomenon and its model representation. This understanding contains elements of both knowledge and know-how, which may be at the core of the unclear notion of a "physical intuition" or "sense" that is said to be relevant for successful model building. Given that in astrophysics most of the classical strategies of model justification for complex, realistic models are not available (analytic solutions, comparison with real-world data, benchmarking with other models), internal model testing that builds on experimenting on models seems to be particularly important. Simple models that may represent in simplified and idealized ways and include only a restricted set of causal factors, therefore, play a crucial role in research as they help in establishing the necessary skills needed to estimate the reliability of complex models that are used to interpret astronomical observations.

5. Conclusion. In this article I have argued for the continuing and indispensable role of simple models in astrophysical target-model comparisons. First, reduced complexity can be epistemically valuable for model instantiation, when the available data are not able to constrain complex astrophysical models with too many unspecified parameters. In particular, the possibility of a systematic search of a simple model's full parameter space can be crucial if multiple solutions in unconnected regions of the parameter space are expected.

Second, simple models also play an important role in the assessment of the structural uncertainty of a given model. In astrophysics, this assessment often relies on an understanding of the complex modeled phenomenon and its model representation, which can be acquired by experimenting on simpler models. The rather vague notions of a "physical intuition" or "refined sense," which are sometimes referred to as important ingredients of successful model building, can be traced back to a sort of understanding containing both elements of explicit knowledge and practical know-how.

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