No Learning from Minimal Models

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This article examines the issue of whether consideration of so-called minimal models can prompt learning about real-world targets. Using a widely cited example as a test case, it argues against the increasingly popular view that consideration of minimal models can prompt learning about such targets. The article criticizes influential defenses of this view for failing to explicate by virtue of what properties or features minimal models supposedly prompt learning. It then argues that consideration of minimal models cannot prompt learning about real-world targets unless one supplements these models with additional information or presuppositions concerning such targets.

1. Introduction. In the recent literature on scientific modeling, several accounts of how consideration of scientific models can prompt learning about real-world targets have been proposed (e.g., Sugden 2000; Cartwright 2009; Mäki 2009). These accounts provide different indications as to what conditions scientific models must satisfy to prompt learning about real-world targets.[1] In spite of these differences, all those accounts are premised on the assumption that consideration of scientific models can prompt learning about real-world targets only if some world-linking relations (e.g., similarity, isomorphism, resemblance) hold between such models and targets. Over the past few years, various authors (e.g., Grüne-Yanoff 2009; Knuuttila 2009) have called this widely shared assumption into question. In their view, mod-

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1. Two sets of accounts are especially prominent. On the one hand, some focus on models' representational functions and contend that consideration of scientific models can prompt learning about real-world targets provided that these models satisfy specific criteria of representational adequacy (see, e.g., Weisberg 2012, on similarity). On the other hand, others argue that highly idealized scientific models can prompt learning about real-world targets by providing credible 'parallel worlds' (e.g., Sugden 2000), mediums for surrogate reasoning (e.g., Suarez 2004), and means of conceptual exploration (e.g., Hausman 1992). These two sets of accounts are not incompatible (e.g., Mäki 2009), yet they provide different indications as to what conditions scientific models must satisfy to prompt learning about real-world targets.

Philosophy of Science, 82 (December 2015) pp. 798–809. 0031-8248/2015/8205-0006$10.00

elers can learn about real-world targets by consideration of so-called *minimal models*, that is, models that "lack any similarity, isomorphism or resemblance relation to the world, [are] unconstrained by natural laws or structural identity, and [do not] isolate any real factors" (Grüne-Yanoff 2009, 83).

Consideration of minimal models is said to prompt learning in the sense that constructing, analyzing, and manipulating these models can justifiably "affect one's confidence in necessity or impossibility hypotheses" about real-world targets without imposing any requirement of similarity, isomorphism, resemblance, and so on, between such models and targets (Grüne-Yanoff 2009, 81). Let us call the thesis that we can learn from minimal models in this sense 'LMM'. If correct, this thesis would have widespread implications for scientific modelers, as necessity and impossibility hypotheses figure prominently in several disciplines. In this article, I examine influential calls in favor of LMM and argue that they fail to withstand scrutiny. Moreover, I draw on a widely cited example of putative learning from minimal models to demonstrate that LMM itself substantially overstates the epistemic import of such models.

The contents are organized as follows. Section 2 criticizes the proponents of LMM for failing to specify by virtue of what properties or features minimal models can supposedly prompt learning about real-world targets. Section 3 purports to demonstrate that, contra LMM, consideration of minimal models cannot prompt learning about real-world targets unless one supplements these models with additional information or presuppositions concerning such targets. Section 4 considers and rebuts three hypothetical defenses of LMM against my critique, namely, the argument from how-possibly explanations, the argument from clusters of models, and the argument from heuristic applications.

Before proceeding, three caveats are in order. First, I shall focus on Grüne-Yanoff's (2009) defense of LMM, since I regard it as one of the most sophisticated cases for this thesis. Still, I shall comment in various places on how my remarks bear on other calls in favor of LMM and putative instances of learning from minimal models. Second, my critique is not intended to suggest that building and manipulating minimal models is a futile modeling exercise. Even so, it challenges the proponents of LMM to both specify by virtue of what properties or features minimal models prompt learning about real-world targets and identify cases where consideration of these models prompts such learning. Finally, the expression 'minimal model' has been used in different senses across disciplines, ranging from set theory to theoretical physics (e.g., Batterman 2002; Weisberg 2007a). Below I employ this expression in the sense indicated by the proponents of LMM unless specified otherwise.[2]

2. I shall occasionally state that minimal models ex hypothesi 'lack any similarity, isomorphism, resemblance, and so on, relation' to real-world targets as an abbreviation for

2. Minimal Models and Learning-Enabling Properties. According to LMM, consideration of minimal models can prompt learning in the sense that constructing, analyzing, and manipulating these models can justifiably "affect one's confidence in necessity or impossibility hypotheses" about real-world targets without imposing any requirement of similarity, isomorphism, resemblance, and so on, between such models and targets (Grüne-Yanoff 2009, 81). Suppose, for the sake of argument, that this constitutes an interesting and informative notion of learning. By virtue of what properties or features can minimal models supposedly prompt such learning?

According to some proponents of LMM, "if we are to learn from a model," then this model "must . . . present a relevant possibility that . . . contradicts an impossibility hypothesis that is held with sufficiently high confidence by the potential learners" (Grüne-Yanoff 2009, 97). That the possibility presented by a model is relevant, in turn, can be established "with reference to natural laws covering this case or to similarity with empirical studies [or to] the credibility of the model" (97). Now, neither 'reference to natural laws' nor 'similarity with empirical studies' can be established on the sole basis of information provided by minimal models. For such models ex hypothesi "lack any similarity, isomorphism or resemblance relation to the world, [are] unconstrained by natural laws or structural identity, and [do not] isolate any real factors" (83). As to the 'credibility' of models, the following remarks are in order.

Various accounts of models' 'credibility' have been provided. The proponents of LMM often draw on Sugden's (2000, 2009) account of credibility on the alleged ground that this account offers "the most relevant arguments supporting the possibility of learning from minimal models" (Grüne-Yanoff 2009, 89). On Sugden's account, a model is *credible* only if it is 'logically consistent' and the scenarios it envisions 'could be real', in the sense that they "cohere with common intuitions and experience" about the general laws and the causal factors operating in modelers' real-world targets (Sugden 2000, 26). That a model is credible in this sense implies neither that the model is true (or approximately true, or probably true, or probably approximately true) nor that it resembles modelers' real-world targets in specific respects. Rather, it only implies that such a model is "compatible with what we know, or think we know, about . . . the real world" (Sugden 2000, 18) and "depicts a possible world, a scenario of how the world could be" (Grüne-Yanoff 2009, 95).

Does the fact that a model is 'credible' in this sense imply that consideration of such a model can per se prompt learning about real-world targets? Not really. After all, some credible models point to merely 'conceivable' or

the characterization of 'minimal models' reported in the text. I expand in section 2 on the differences between distinct characterizations of 'minimal model' and the implications of such differences for the tenability of LMM.

'logically possible' scenarios, mechanisms, and so on, that, for all modelers know, do not characterize the workings or the properties of any real-world target (e.g., Weisberg 2007b). This, in turn, makes it doubtful that consideration of credible models can per se prompt learning about real-world targets unless these models provide some information or make some presuppositions concerning such targets. To be sure, one may agree that credibility judgments "are often elicited solely through consideration of imaginary worlds" (Grüne-Yanoff 2009, 94) and that judging a model to be credible does not require one to demonstrate this model's putative similarity, isomorphism, or resemblance relation with any real-world target (95). Still, some information or presupposition about real-world targets is needed if one is to justifiably take facts about the possible worlds posited by a credible model to stand for putative facts about such targets.[3]

These considerations have critical implications for the tenability of LMM. To see this, recall that minimal models ex hypothesi lack any similarity, isomorphism, resemblance, and so on, relation to real-world targets. As this definition indicates, consideration of a minimal model can per se provide neither empirical nor a priori reasons to justifiably infer that what is possible (or necessary) in the worlds posited by such a model is also possible (or necessary) in the real-world situations targeted by modelers. For this reason, modelers have to supplement minimal models with some information or presuppositions concerning their real-world targets, if they are to justifiably take these models' necessity and impossibility results to hold also in the real-world situations they target. More generally, it appears that consideration of minimal models cannot prompt learning about real-world targets unless one supplements such models with additional information or presuppositions concerning those targets.

A proponent of LMM might deny that one has to specify by virtue of what properties or features minimal models can supposedly prompt learning about real-world targets. After all—the thought would be—what this learning-enabling property or feature is presumably depends on contextual factors such as modelers' aims, what information is available concerning the investigated targets, and so on. The latter observation is not without merit, but it does not exempt the proponents of LMM from the need to explicate by virtue of what properties or features minimal models can supposedly prompt learning. For the alleged context dependency of what these properties or features are implies neither that any property or feature may enable learning nor

3. In this respect, it is telling that modelers often supplement their credibility judgments with some empirical illustrations or 'stories' explicating how the entities and mechanisms posited by their models may be taken to operate in the examined real-world situations (e.g., Morgan 2001).

that whether specific minimal models possess learning-enabling properties or features is an arbitrary matter. Similarly, observing that scientific modelers occasionally take their models to prompt learning about real-world targets even in cases where the relation between such models and targets is uncertain or undetermined (e.g., Grüne-Yanoff 2009, 83) would hardly help the proponents of LMM. For this observation by no means implies that models can prompt learning about real-world targets in the absence of world-linking relations.

At this stage, a proponent of LMM might contend that all LMM was meant to assert is simply that consideration of minimal models, supplemented with some additional information or presuppositions concerning real-world targets, can prompt learning about those targets. Let us call this weaker assertion 'LMM*' so as to distinguish it from LMM. LMM* appears to be far less controversial than LMM. Unfortunately, LMM* also seems to trivialize the issue of whether we can learn from minimal models. After all, no sensible modeler would deny that consideration of minimal models—supplemented with suitably detailed information and presuppositions about real-world targets—can prompt learning about such targets. Moreover, if LMM* was all the proponents of LMM intended to show, then speaking of 'learning from minimal models' would appear to be rather misleading. For on LMM* consideration of minimal models is said to prompt learning about real-world targets only in an indirect and derivative sense. That is to say, while a literal reading of LMM seemingly fails to withstand scrutiny, the proponents of LMM have hitherto failed to identify and substantiate a nontrivial reformulation of such a thesis.[4]

3. Putative Instances of Learning from Minimal Models. The critique put forward in the previous section challenges the proponents of LMM to identify and substantiate a nontrivial reformulation of this thesis. In this section, I complement this challenge by arguing that consideration of minimal models cannot per se prompt learning about real-world targets. In particular, I aim to demonstrate that LMM falls prey to the following dilemma. On the one hand, truly minimal models lack the evidential and epistemic resources

4. A reformulation of LMM counts as 'trivial' if it gives the question whether we can learn from minimal models an answer that is straightforwardly determinable on the basis of our background knowledge or available evidence. Several reformulations of LMM would count as trivial in this sense. For instance, consider the hypothetical reformulation of LMM as the thesis that highly idealized models can prompt learning about real-world targets. This reformulation of LMM trivializes the issue of whether we can learn from minimal models by redefining the notion of 'minimal model' in such a way that models that have already been shown to prompt learning about real-world targets (e.g., Sugden 2000; Godfrey-Smith 2006) count as 'minimal models'.

to prompt learning about real-world targets. On the other hand, several models that prima facie seem minimal can prompt learning about real-world targets, but they succeed in doing so only if supplemented with additional information or presuppositions about such targets. Below I illustrate this dilemma with regard to a widely cited example of a purportedly minimal model, namely, Schelling's (1969, 1971) checkerboard model of residential segregation. More specifically, I first outline Schelling's model and explicate in what sense this model is said to prompt learning about real-world targets. I then argue that even this widely cited example of putative learning from minimal models fails to support LMM.[5]

Schelling presents his checkerboard model as "an abstract exploration of some of the quantitative dynamics of segregating behaviour" (1971, 148). In Schelling's model, two types of tokens are initially distributed randomly over a checkerboard. These tokens represent two types of individuals, and the checkerboard represents a city. Each individual's neighborhood is defined as the set of grid elements adjacent to the cell occupied by the individual (Moore neighborhood). The dynamics of the model is as follows. Individuals sequentially choose to either remain in place or move to nearby unoccupied cells. Each individual's decision depends on whether her preference to have at least 30% of neighbors of the same type as her is satisfied. If this is the case, the individual remains where she is. Otherwise, the individual moves to the nearest unoccupied cell where her preference is satisfied. This sequence of decisions continues until all individuals' preferences are satisfied.

Schelling demonstrates that an abstract pattern of segregation—that is, a pattern of segregation figuring in the possible worlds envisioned by his model—can emerge even from individuals' mild preference not to be in a minority in the neighborhood in which they live. As documented by subsequent studies, this result is remarkably robust across changes in individuals' tolerance thresholds for individuals of a different type, neighborhood sizes, and spatial configurations (e.g., Pancs and Vriend 2007). Indeed, segregation may emerge even in cases where individuals strictly prefer to live in diverse communities and be surrounded by agents of a different type (e.g., Muldoon, Smith, and Weisberg 2012). Schelling's original model is often claimed to provide "a good example" of how minimal models can prompt learning about real-world targets (e.g., Grüne-Yanoff 2009, 96). Two issues regarding this claim are usefully distinguished. First, is Schelling's checkerboard model minimal? And second, does consideration of this model (on the

5. I focus on Schelling's model of residential segregation because the proponents of LMM have discussed this model in great detail. My critique holds mutatis mutandis for other instances of putative learning from minimal models (see, e.g., Knuuttila 2009, on Tobin's ultra-Keynesian model).

supposition that such a model is minimal) prompt learning about real-world targets?

Schelling's checkerboard model does not directly represent an actual segregation process in any real-world city. In particular, it disregards features that are often associated with real-world segregation processes (e.g., interactions across neighborhoods) and does not include well-known causes of real-world segregation (e.g., interpersonal welfare differences). Even so, it is questionable whether Schelling's model is minimal in the sense indicated by LMM. To be sure, one might reiterate that "neither similarity, isolation nor conforming to regularity are explicit concerns in Schelling's original paper" (Grüne-Yanoff 2009, 88). This, however, by no means implies that Schelling's model actually "lack[s] any similarity, isomorphism or resemblance relation to the world, [is] unconstrained by natural laws or structural identity, and [does not] isolate any real factors" (83). Furthermore, there are reasons to question whether Schelling's model is minimal in this sense. For example, the possible worlds posited by such a model seem to resemble both real-world cities and real-world segregation processes in several respects (e.g., checkerboard's division in neighborhoods, dependency of individuals' actions on whether their preferences are satisfied).

Let us suppose, for the sake of argument, that Schelling's model is minimal in the sense indicated by LMM. Various authors take Schelling's demonstration that abstract segregation can emerge from individuals' preference not to be in a minority in the neighborhood they live in to prompt learning about real-world segregation processes. Their reasoning goes as follows. Before the publication of Schelling's model, "many people believed that segregation is necessarily a consequence of explicitly racist preferences" (Grüne-Yanoff 2009, 96). Schelling's demonstration undermines this widespread belief, thereby leading all those who endorsed such a belief to justifiably reduce their confidence in it. This, in turn, constitutes learning in the sense indicated by LMM.

There are at least two reasons to doubt that this reasoning shows that consideration of Schelling's model (on the supposition that such a model is minimal) prompts learning about real-world segregation processes. First, it is doubtful that at the time when this model was published many people believed that segregation is necessarily a consequence of explicitly racist preferences. And second, Schelling's demonstration that abstract segregation is not necessarily a consequence of explicitly racist preferences does not per se prompt justified changes in confidence in hypotheses about any real-world segregation process. Let us consider these two issues in turn.

Before the publication of Schelling's model, many people presumably believed that residential segregation is often—or even typically—caused by explicitly racist preferences. This, however, falls short of implying that many (or even some) people endorsed the much stronger hypothesis that segregation is necessarily a consequence of explicitly racist preferences. Moreover, it is doubtful that this hypothesis was widely held at the time when Schelling published his model. For several factors other than explicitly racist preferences were already well-known possible causes of segregation at that time (see, e.g., Schelling 1969, on interpersonal welfare differences).

Suppose, for the sake of argument, that at the time when Schelling's model was published, many people believed that segregation is necessarily a consequence of explicitly racist preferences. Would this imply that Schelling's model prompts learning in the sense indicated by LMM? It does not seem so. To be sure, Schelling's demonstration that even mild discriminatory preferences can foster abstract segregation may prompt a justified change in confidence in hypotheses about the segregation processes figuring in the possible worlds posited by his model. This contribution might be epistemically valuable to modelers. However, it does not per se constitute learning in the sense indicated by LMM, since it does not imply a justified change in modelers' confidence in hypotheses about any real-world segregation process (Sugden 2000, 17).

4. Replies and Further Objections. A proponent of LMM may concede that prominent calls in favor of this thesis face significant difficulties. At the same time, she might attempt to substantiate LMM by showing that consideration of minimal models can prompt learning about real-world targets even in cases where these models are not supplemented with additional information or presuppositions concerning such targets. In this section, I consider and rebut three arguments one might develop to defend LMM against my critique. More specifically, I address in turn the argument from how-possibly explanations, the argument from clusters of models, and the argument from heuristic applications.

4.1. How-Possibly Explanations. The argument from how-possibly explanations builds on the following distinction between how-actually and how possibly explanations. How-actually explanations identify what events or factors in fact cause the occurrence or specific properties of the investigated phenomena. How-possibly explanations, instead, merely identify possible causes of those phenomena's occurrence or properties (e.g., Reiner 1993). Now, modelers are frequently unable to provide how-actually explanations of the phenomena they investigate and rely on a menu of how-possibly explanations (e.g., Ylikoski and Aydinonat 2014). Consideration of minimal models may help modelers identify previously overlooked possible causes of the investigated phenomena, thereby extending the set of how-possibly explanations available to them. This contribution, in turn, might lead modelers to justifiably change their confidence in specific hypotheses about real-world targets. Hence, the reasoning goes, consideration of minimal models can prompt learning about such targets.[6]

To assess the cogency of this reasoning, let us consider again Schelling's checkerboard model of residential segregation. As noted in section 3, this model demonstrates that abstract segregation patterns can emerge from individuals' mild preference not to be in a minority in the neighborhood in which they live. Individuals' mild discriminatory preferences are unlikely to be the most prominent cause of real-world segregation processes. Even so, they may foster real-world segregation when other contributing factors (e.g., organized discrimination) are in place, and they might arguably do so even in the absence of such factors. In light of these remarks, a proponent of LMM might hold that Schelling's model identifies previously overlooked possible causes of segregation and thereby extends the set of available how-possibly explanations of real-world segregation (e.g., Grüne-Yanoff 2013a).

Suppose that Schelling's model extends the set of how-possibly explanations of segregation available to modelers by identifying previously overlooked possible causes of abstract segregation. This contribution may be epistemically valuable to modelers but does not per se foster justified changes in confidence in hypotheses concerning real-world segregation processes. A proponent of LMM might retort that modelers can occasionally demonstrate that the possible causes of abstract segregation identified by Schelling's model can foster segregation also in the real-world situations they investigate. Still, on the supposition that Schelling's model is minimal, this demonstration would require modelers to supplement such a model with information or presuppositions concerning those real-world situations (sec. 3). More generally, it is hard to see how exactly consideration of a minimal model could per se establish that what counts as a possible cause of a phenomenon in the possible worlds posited by this model is a possible cause of such a phenomenon also in real-world situations.

4.2. Clusters of Models. Until recently, philosophical discussions of the epistemic import of scientific models have predominantly focused on individual models. For their part, some authors have maintained that the epistemic import of scientific models is best understood with reference to clusters of models relevant to the modelers' aims (e.g., Godfrey-Smith 2006;

6. The expression 'how-possibly explanations' was initially used by Dray (1957, 1968) to designate explanations that aim to account for how events whose occurrence was formerly deemed to be impossible could have occurred. Here I use such an expression to indicate explanations that identify possible causes of the investigated phenomena, irrespective of whether the occurrence of these phenomena was formerly deemed to be impossible.

Weisberg 2007a).[7] A proponent of LMM might draw on these observations to argue that even if individual minimal models fail to prompt learning about real-world targets, clusters of minimal models can prompt such learning by demonstrating that the implications of specific minimal models can be derived by means of several independent assumptions.

These considerations point to the so-called derivational robustness of models' implications, that is, the degree to which these implications hold under variations in the assumptions used to derive them (Woodward 2006). Demonstrating that a model's implications are derivationally robust is often taken to provide some form of epistemic support to such implications (e.g., Weisberg 2006). In particular, various authors hold that models' implications frequently rest on unrealistic assumptions and that derivational robustness analyses can justifiably increase modelers' degree of confidence in the robust theorems that connect these assumptions to specific modeling results (e.g., Kuorikoski, Lehtinen, and Marchionni 2010). Building on these claims, a proponent of LMM may suggest that modelers can justifiably increase their confidence in hypotheses about real-world targets by relying on clusters of minimal models.

Now, one may grant that modelers can gain informative insights concerning the behavior or the features of their targets by relying on clusters of models, as opposed to individual models. However, appealing to derivational robustness does not help the proponents of LMM substantiate their thesis. To see this, suppose facing a situation where modelers rely on a cluster of minimal models. Consideration of a cluster of minimal models may prompt justified changes in modelers' confidence in hypotheses concerning the possible worlds posited by these models. However, it cannot prompt justified changes in modelers' confidence in hypotheses concerning real-world targets unless one supplements at least some of these minimal models with additional information or presuppositions about such targets. For minimal models ex hypothesi lack any similarity, isomorphism, resemblance, and so on, relation to real-world targets. And consideration of those models cannot per se justifiably increase modelers' confidence that the results obtained in the possible worlds posited by such models hold also in the real-world situations they target (sec. 2).

4.3. Heuristic Applications. The argument from heuristic applications proceeds as follows. Minimal models often have informative heuristic applications, in the sense that they inspire novel hypotheses about modelers'

7. The expression that models 'come into clusters' has been used in different senses. Below I employ this expression to indicate situations where modelers' predictive and explanatory goals are best achieved by using a combination of structurally dissimilar models.

targets and suggest more precise formulations of former hypotheses about such targets (e.g., Grüne-Yanoff 2013b). By themselves, neither inspiring novel hypotheses nor suggesting more precise formulations of former hypotheses constitutes learning in the sense indicated by LMM (Grüne-Yanoff 2009, 85). Even so, minimal models' heuristic applications could indirectly foster justified changes in confidence in hypotheses about real-world targets. For instance, consideration of minimal models may lead modelers to form novel beliefs about real-world targets, which in turn challenge specific hypotheses concerning such targets. Hence, the reasoning goes, consideration of minimal models can prompt learning about real-world targets even in cases where these models are not supplemented with additional information or presuppositions regarding such targets.

Suppose, for the sake of argument, that consideration of minimal models occasionally inspires novel hypotheses about modelers' targets and suggests more precise formulations of former hypotheses about such targets. Still, it remains unclear how exactly heuristic applications based solely on minimal models could prompt learning about real-world targets unless one supplements the minimal models on which these heuristic applications are based (or those heuristic applications themselves) with additional information or presuppositions concerning such targets. In this respect, the proponents of LMM may well insist that heuristic applications of minimal models can foster justified changes in confidence in hypotheses concerning the possible worlds posited by such models. However, the point remains that heuristic applications based solely on minimal models cannot prompt justified changes in confidence in hypotheses about real-world targets in the absence of information or presuppositions regarding such targets.

5. Conclusion. Consideration of minimal models can provide modelers with epistemically informative insights about the possible worlds posited by these models. However, it cannot prompt learning about real-world targets unless one supplements those models with additional information or presuppositions concerning such targets. The proponents of LMM have hitherto failed to demonstrate that models can prompt learning about real-world targets in the absence of world-linking relations between such models and targets. In particular, LMM appears to overstate the epistemic import of minimal models even with regard to widely cited examples of putative learning from minimal models.

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