

1 A causal approach to analogy¹

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3 Abstract: Analogical reasoning addresses the question how evidence from various phenomena
4 can be combined and made relevant for theory development and prediction. In the first part of
5 my contribution, I review some influential accounts of analogical reasoning, both historical
6 and contemporary, focusing in particular on Keynes, Carnap, Hesse, and more recently
7 Bartha. In the second part, I sketch a general framework. To this purpose, a distinction
8 between a predictive and a conceptual type of analogical reasoning is introduced. I then take
9 up a common intuition according to which (predictive) analogical inferences hold if the
10 differences between source and target concern only irrelevant circumstances. I attempt to
11 make this idea more precise by addressing possible objections and in particular by specifying
12 a notion of causal irrelevance based on difference making in homogeneous contexts.

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31 **1. Introduction**

32 When evidence from different phenomena is combined in order to predict, to explain or to
33 develop a conceptual framework, this can often be understood in terms of analogical
34 reasoning. After all, analogical inferences, according to a typical explication, are inferences
35 based on similarity: If two phenomena, source A and target A*, are similar and A has a

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1 characteristic C, then under certain circumstances it is plausible or probable to assume that A*
2 has characteristic C as well.

3 At all times in history, scientists have stressed the epistemological significance of analogy,
4 including such luminaries as William Gilbert, Johannes Kepler, Joseph Priestley, or James
5 Clerk Maxwell. Johannes Kepler, for example, wrote in his *Opticks*: “I cherish more than
6 anything else the Analogies, my most trustworthy masters. They know all the secrets of
7 nature.” (Kepler 1604; cited in Polya 1954, p. 12) And indeed, analogical reasoning was a
8 major source of creativity in Kepler’s scientific method. In his analysis of the solar system, he
9 crucially relied on the analogy between the emission of light and the propagation of what he
10 called the *anima motrix*, i.e. the spirit that moves the planets around the sun:

11 “Let us suppose, then, as is highly probable, that motion is dispensed by the Sun in the
12 same proportion as light. Now the ratio in which light spreading out from a center is
13 weakened is stated by the opticians. For the amount of light in a small circle is the
14 same as the amount of light or of the solar rays in the great one. Hence, as it is more
15 concentrated in the small circle, and more thinly spread in the great one, the measure
16 of this thinning out must be sought in the actual ratio of the circles, both for light and
17 for the moving power [motrice virtute].” (Kepler, 1596/1981, p. 201, cited in Gentner
18 et al. 1997, p. 414-415)

19 Thus, the analogy suggests that the *anima motrix*, just as light, constitutes a conserved
20 quantity acting according to an inverse square law. The example demonstrates well, how
21 evidence from two different sources, i.e. the theory of optical phenomena and
22 phenomenological knowledge about the solar system, can be combined in order to develop a
23 model concerning the interaction of material bodies in the solar system.

24 As another example of analogical reasoning in the sciences, consider animal models that are
25 used in medicine and pharmacology to determine the efficacy of a treatment in human beings.
26 Again, evidence from disparate phenomena, here mice and human beings, is amalgamated to
27 further the knowledge about these phenomena. I will argue later that this example is different
28 from the previous one in important respects. Most importantly, it aims at prediction, while
29 Kepler was primarily concerned with theory or model development.

30 In view of these examples of successful scientific practice, it is remarkable that influential
31 authors have questioned, whether there are any universal rules governing analogical
32 inferences.² For example, Paul Bartha, who has written the most extensive modern-day
33 treatise on analogical reasoning (2010), states: “Despite the confidence with which particular
34 analogical arguments are advanced, nobody has ever formulated an acceptable rule, or set of
35 rules, for valid analogical inferences. There is not even a plausible candidate.” (Bartha 2013,
36 Sec. 2.4) In a similar vein, Patrick Maher writes: „Argument by analogy is a generally
37 accepted form of inductive reasoning and many think that inductive reasoning can be
38 represented using the probability calculus. From these facts one might expect that there would

² Note that the absence of universal rules for analogical inferences does not necessarily imply that such inferences cannot be reliable. An interesting proposal in this regard is John Norton’s *material theory of induction* (cp. Norton 2011 and references therein). A critique of Norton’s theory of induction is beyond the scope of this paper.

1 be accepted probability models that can represent inference by analogy, but no such model
2 exists.” (Maher 2001, p. 183) As an example from the statistics and computer science
3 literature, Henri Prade and Gilles Richard write in their recent overview of the field:
4 “analogical reasoning is not amenable to a formal framework in a straightforward manner due
5 to the brittleness of its conclusions.” (2014, 5)

6 The most pressing and interesting epistemological problem with respect to reasoning by
7 analogy therefore is how to bring these two aspects together, on the one hand, the ubiquitous
8 use of analogy in scientific practice and, on the other hand, the widespread belief that a
9 formal framework for analogical inferences does not exist.

10 In the next section, relying on short case studies from the history of scientific method, I argue
11 for three interrelated points. First, I briefly present Carnap’s framework of induction, building
12 mainly on enumerative induction. While he tries to implement analogical reasoning in his
13 approach, he fails to find a convincing manner to do so. This situation leads me to argue for a
14 general failure of enumerative approaches to implement analogical reasoning. Instead,
15 eliminative approaches, focusing on the variation of circumstances rather than the repetition
16 of instances as in enumerative induction, are much more amenable to analogical reasoning, as
17 the second case study on Keynes’ approach to induction shows. Third, I introduce two
18 influential contemporary frameworks by Mary Hesse and Paul Bartha, which address one of
19 the major problems of Keynes’ approach, the so-called counting problem. To this purpose,
20 they develop a two-dimensional framework, which takes into account the ‘horizontal’
21 similarities between different phenomena, but also the ‘vertical’ nature of the relations
22 between similarities and differences.

23 In the third section, a distinction between two types of analogical reasoning is introduced,
24 namely conceptual and predictive analogies. These differ in their epistemic aim, the nature of
25 the vertical relations, the criteria of evaluation, and the methodological framework. I argue
26 that the widespread skepticism concerning analogical inferences partly results from a failure
27 to recognize this distinction. While conceptual analogies indeed are not amenable to a formal
28 framework to determine the truth or probability of such inferences, this is not the case for
29 predictive analogies.

30 In section four, I then sketch a framework for predictive analogies building on the intuition
31 that ‘a predictive analogical inference holds, if the differences between source and target are
32 irrelevant to the prediction’. I discuss some preliminary objections and argue that irrelevance
33 must be understood in causal terms. Examining different explications of the notion of causal
34 irrelevance from the literature, I find none of them suitable for the context of analogical
35 reasoning. My own proposal construes causal irrelevance in terms of difference making in a
36 given background context.

37 Since the framework that was developed so far is intended for deterministic situations, I
38 briefly address in section five, how it can be extended to include probabilistic analogical
39 inferences. While there are straightforward ways to implement probability, a crucial problem
40 remains regarding the interpretation of probability in this context.

41

1 2. Three historical perspectives

2 The history of methodological thinking about analogy is quite rich. In the following, I
3 concentrate on three more recent episodes or case studies how methodologists have
4 approached analogical reasoning. These will provide the groundwork for the approach to be
5 outlined later in the article.

6 2a. Carnap and the inadequacy of enumerative approaches

7 Rudolf Carnap developed one of the most extensive and detailed inductive frameworks in the
8 20th century, in which he explicitly aimed to include considerations of analogy. Carnap's
9 approach is based on a confirmation function $c(h|e)$, which designates the confidence in a
10 hypothesis h based on some evidence e . As is well-known, Carnap was a dualist about
11 probability, distinguishing an empirical and a logical role of probability—the former
12 regarding relative frequencies while the latter is usually identified with rational degree of
13 belief in a hypothesis based on some evidence.

14 Carnap construes analogical inferences as inductive inferences from one individual to another
15 based on their known similarity, much in line with the general understanding that was
16 presented in the introduction: “The evidence known to us is the fact that individuals b and c
17 agree in certain properties and, in addition, that b has a further property; thereupon we
18 consider the hypothesis that c too has this property.” (1950, p. 569)

19 Carnap's general approach to induction is based on what is often called the ‘straight rule’ of
20 induction: Given a family of predicates P , i.e. a mutually exclusive but exhaustive group of
21 predicates that applies to a number of individuals, the degree of confirmation corresponds to
22 the relative frequency s_j/s of a property P_j in the first s individuals. In other words, the straight
23 rule of induction is just ordinary enumerative induction. Carnap recognizes the deficiencies of
24 this simple rule and consequently extends it to ‘a continuum of inductive methods’ which is
25 determined by a number of additional parameters. There are several versions in his writing
26 over the course of his life, the best known being the so-called λ - γ system developed in his
27 mature, posthumously published *Basic System of Inductive Logic* (1971, 1980) with a
28 confirmation function

$$c_j(s_1, \dots, s_k) = \frac{s_j + \lambda \gamma_j}{s + \lambda}.$$

29 Here, $s = s_1 + \dots + s_k$ can be interpreted as the number of real individuals and λ the number of
30 virtual individuals. Among the former s_j have the property P_j , among the latter $\lambda \gamma_j$. This
31 confirmation function can be rewritten in terms of an empirical and a logical part:

$$c_j(s_1, \dots, s_k) = \frac{s}{s + \lambda} \frac{s_j}{s} + \frac{\lambda}{s + \lambda} \gamma_j$$

32 For large s , the empirical part dominates, for small s , the logical part. Thus, the logical part
33 can be interpreted as an *a priori* contribution to the confirmation function.

34 In general, analogical influence is considered to belong to this logical part. Carnap specifies
35 several kinds of analogical influence. First, he draws a distinction between similarity

1 influence, which takes into account the distance between properties, and proximity influence
 2 referring to the distance between individuals—presupposing in both cases that an adequate
 3 metric exists. With respect to the former, Carnap further distinguishes between analogical
 4 influence within one predicate family and that between different predicate families. While he
 5 acknowledges that the latter is much more common than the former, he mainly addresses in
 6 the *Basic System* analogical influence within one predicate family, presumably because it is
 7 the simpler problem (for a very brief discussion of analogical influence between different
 8 predicate families, see Carnap 1950, §110 D). Furthermore, Carnap’s analysis of analogy is
 9 restricted to individuals which have certain properties in common, while in typical analogical
 10 inferences individuals are also known to differ in certain other properties—a critique spelled
 11 out in some detail by Mary Hesse (1964).

12 Carnap suggests treating analogical inferences in terms of the mentioned γ corresponding to
 13 the width (or weight) of properties and an additional η corresponding to the distance between
 14 properties. If two properties P_1 and P_2 are sufficiently similar, i.e. are close in terms of the
 15 distance measure, then the relative frequency of P_1 will influence the confirmation function
 16 for P_2 and vice versa. Naturally, the width also has to be taken into account: basically, the
 17 more weight a property has, the greater its influence. According to Carnap, such analogy
 18 influence “is usually very small”, it “decreases with increasing [evidence in terms of number
 19 of individuals] s ”, and therefore can “be practically neglected” if s is large (1980, p. 41). To
 20 repeat, this is because analogy influence belongs to the logical and a priori part of the
 21 confirmation function, which can be neglected for $s \gg \lambda$. As an example, Carnap uses the
 22 color space to illustrate the concepts of width, essentially the range or variation subsumed
 23 under a specific color, and distance, i.e. the perceived similarity between different colors.
 24 Both are determined by the chosen metric of the color space (1980, Sec. 14.A).

25 Carnap’s treatment of analogy remains brief and fragmentary—in contrast to his very detailed
 26 treatment of induction in general—and this situation may already cast doubt over the
 27 suitability of enumerative approaches to analogy, i.e. essentially those approaches that are
 28 based on some version of the straight rule. There have since been a number of attempts to
 29 integrate analogical reasoning within an essentially Carnapian approach to inductive logic
 30 (e.g. Hesse 1964, Kuipers 1984, Romeijn 2006, Maher 2001). It seems fair to say that no
 31 agreement has been reached (for a helpful overview, see Huttegger forthcoming). Many
 32 decades after Carnap published his approach to inductive logic, it continues to be doubtful
 33 whether his framework is capable to cover analogical reasoning in a sensible manner.

34 One strain of criticism attacks the use of additional parameters such as γ or η which must be
 35 derived from a metric over properties, which rarely is explicitly available. These parameters
 36 seem considerably ad hoc as is well illustrated by the example of the color space for which a
 37 wide variety of representations are possible (Reibe & Steinle 2002). In fact, this situation has
 38 led Wolfgang Stegmüller, a close collaborator of Carnap, to suggest that Carnap is really
 39 talking about subjective rather than logical probability (Stegmüller 1973, 514)—which would
 40 further undermine any attempt to justify reliable predictions based on analogical reasoning,
 41 even though these are ubiquitous in the sciences, as the examples from the introduction
 42 suggest.

1 In the end, what seems the most problematic aspect about Carnap's approach is its focus on
 2 the straight rule and on relative frequencies as the core concepts for confirmation—
 3 automatically confining analogy to prior considerations, which wash out as increasing
 4 evidence in terms of instances is gathered.³ After all, scientific practice suggests otherwise:
 5 relative frequencies are generally a bad indicator for confirmation, while analogies can often
 6 provide highly reliable evidence. The lesson from the case study on Carnap's treatment of
 7 analogy thus seems to be that just as enumerative approaches to induction in general,
 8 enumerative approaches to analogy, confining analogy to prior considerations, run into deep
 9 and presumably unsolvable problems.

10 *2b. Keynes and the ubiquity of analogical reasoning*

11 It is often thought that the essence of inductive reasoning lies in the multiplication of
 12 instances and Carnap's approach with its reliance on the straight rule and on relative
 13 frequencies attempts to formalize this intuition. However, there has been for many centuries
 14 an alternative tradition of inductive reasoning which focuses on the variation of circumstances
 15 rather than on the number of instances. Proponents of this later tradition, which is sometimes
 16 referred to as eliminative induction, are among others Francis Bacon, John Stuart Mill and
 17 more recently John Maynard Keynes. It turns out that its basic inductive framework is much
 18 more amenable to analogical reasoning. After all, an analogical inference concludes from one
 19 instance with certain circumstances to another with different circumstances. Indeed,
 20 proponents of eliminative induction have often considered analogical inference as the core of
 21 inductive reasoning. The best example in this regard is John Maynard Keynes, who in his
 22 *Treatise on Probability* lays out a general framework for induction based on analogy:

23 „In an inductive argument, therefore, we start with a number of instances similar in
 24 some respects AB, dissimilar in others C. We pick out one or more respects A in
 25 which the instances are similar, and argue that some of the other respects B in which
 26 they are also similar are likely to be associated with the characteristics A in other
 27 unexamined cases. The more comprehensive the essential characteristics A, the greater
 28 the variety amongst the non-essential characteristics C, and the less comprehensive the
 29 characteristics B which we seek to associate with A, the stronger is the likelihood or
 30 probability of the generalisation we seek to establish.” (Keynes 1921, 219-220)

31 Note again that Keynes's description closely resembles what we had defined as an analogical
 32 argument in the introduction, while he considers it the fundamental form of an inductive
 33 argument. Keynes introduces some terminology that has since become standard in the
 34 literature on analogical reasoning. The *positive analogy* concerns those properties which
 35 source and target have in common, the *negative analogy* those properties in which source and
 36 target differ, and the *unknown analogy* those properties of which it is yet unknown whether
 37 they belong to the positive or negative analogy. Finally, the *hypothetical analogy* concerns

³ Note that Bayesian approaches to confirmation often assume a similar role for analogy as being confined to prior considerations (e.g. Salmon 1990): “I suspect that the use of arguments by analogy in science is almost always aimed at establishing prior probabilities. [...] The moral I would draw concerning prior probabilities is that they can be understood as our best estimates of the frequencies with which certain kinds of hypotheses succeed. These estimates are rough and inexact...” (186-187).

1 those properties which are known of the source phenomenon and predicted of the target
2 phenomenon (see also Bartha 2013).

3 Keynes' approach to induction turns the Carnapian view upside down.⁴ While for Carnap
4 enumerative induction in the form of the straight rule is central and analogy is confined to
5 prior considerations that wash out with increasing evidence, for Keynes, analogical inferences
6 are fundamental and enumerative induction only plays a subordinate role by controlling for
7 circumstances whose influence thus far has not been explicitly considered:

8 “The object of increasing the number of instances arises out of the fact that we are
9 nearly always aware of *some* difference between the instances, and that even where the
10 known difference is insignificant we may suspect, especially when our knowledge of
11 the instances is very incomplete, that there may be more. Every new instance *may*
12 diminish the unessential resemblances between the instances and by introducing a new
13 difference increase the Negative Analogy. For this reason, and for this reason only,
14 new instances are valuable.” (Keynes 1921, 233)

15 Relatedly, Keynes denies that relative frequencies can be used to determine probabilities
16 along the lines of the straight rule. The reason is that instances vary in different ways
17 regarding their circumstances and thus there is usually no reason to count them with equal
18 weight as the straight rule presupposes:

19 „I do not myself believe that there is any direct and simple method by which we can
20 make the transition from an observed numerical frequency to a numerical measure of
21 probability.” (Keynes 1921, 367)

22 In summary, Carnap's system implements a clear distinction between enumerative induction
23 and analogy, it confines analogical influence to a priori considerations, and it endorses a
24 principle of instantial relevance (“one of the basic characteristics of customary inductive
25 reasoning”, Carnap 1971, 161), according to which any positive instance strictly increases the
26 confirmation function that the next instance is positive as well.⁵ All this is incompatible with
27 Keynes's approach, who argues that all induction basically relies on analogy, even seeming
28 applications of enumerative induction actually aim at increasing the negative analogy. He
29 rejects any simple frequentist approach to confirmation, which quantifies confirmation based
30 on some variant of the straight rule. Relatedly, he rejects the principle of instantial relevance:
31 in particular, if two instances are fully identical in all their relevant circumstances, then the
32 additional instance does not confirm at all (1921, 233).

33 Unfortunately, the shift away from enumerative induction to an inductive framework based on
34 analogy, while conceptually sensible, eliminates the most obvious candidates for a measure of
35 confirmation, namely the number of positive instances or relative frequencies. Instead, a
36 quantitative measure could consist in a weighted comparison between positive and negative
37 analogy. Bartha suggests the following characterization of this widespread intuition:

⁴ i.e. systematically speaking, historically of course Keynes was prior to Carnap.

⁵ Carnap qualifies that the strict inequality only holds if the original confirmation function is not zero or one.

1 “Suppose S and T are the source and target domains. Suppose P_1, \dots, P_n (with $n \geq 1$)
 2 represents the positive analogy, A_1, \dots, A_r and $\neg B_1, \dots, \neg B_s$ represent the (possibly
 3 vacuous) negative analogy, and Q represents the hypothetical analogy. In the absence
 4 of reasons for thinking otherwise, infer that Q^* holds in the target domain with degree
 5 of support $p > 0$, where p is an increasing function of n and a decreasing function of r
 6 and s .” (2013, Sec. 2.4)

7 But, as many authors including Bartha have stressed, this approach leads to the notorious
 8 *counting problem*. While counting instances in enumerative induction seems straight-forward,
 9 counting properties in analogical reasoning is not. If two instances have property ‘color’ in
 10 common, but differ in property ‘size’, how possibly should one compare color and size? It
 11 appears impossible to formulate general rules for this task, which has led many to conclude
 12 that analogical reasoning is necessarily contextual. As a result, Keynes’ approach remains
 13 almost entirely qualitative, which may have contributed to the fact that it is barely used in
 14 contemporary science.

15 Still, Keynes does derive some general guidelines for analogical reasoning. Inductive
 16 arguments which conclude from a number of examined instances to a generalization can be
 17 strengthened by the following means:

- 18 - “by reducing the resemblances known to be common to all the instances, but ignored
 19 as unessential by the generalization,
- 20 - by increasing the differences known to exist between the instances,
- 21 - by diminishing the sub-analogies or unessential resemblances known to be common to
 22 some of the instances and not known to be false of any.” (Keynes 1921, 231-232)

23 For this, either new instances have to be examined or the knowledge of familiar instances has
 24 to be extended. Most standard treatments of analogical reasoning propose similar qualitative
 25 guidelines (see Bartha 2013, Sect. 3.1 for a comprehensive list of commonsense guidelines).

26 In summary, Keynes’ framework bases inductive reasoning on analogical inferences, i.e.
 27 every inductive inference is conceived as an inference based on similarity. While this is
 28 conceptually plausible, proponents have largely failed to come up with a quantitative
 29 confirmation measure for such an approach.⁶

30 *2c. Hesse, Bartha and the two-dimensional approach*

31 No solution to the counting problem seems to be forthcoming. Apparently, how properties are
 32 counted very much depends on the specific context. There is, however, one crucial insight that
 33 has occasionally been pointed out in discussions of analogical reasoning, but that was most
 34 forcefully stressed by Mary Hesse and more recently by John Norton and Paul Bartha. For
 35 analogical reasoning it is important to not only consider the similarity and differences in

⁶ While the approach proposed in this essay builds on Keynes’ ideas in many ways, one of the advantages with respect to Keynes is that to some extent it is quantitative. In particular, a sufficient and necessary criterion is given for analogical inferences in deterministic contexts. Thus, analogical inferences fulfilling this criterion are valid with probability 1. In Section 5, an extension of the proposed framework is briefly sketched, under which circumstances one can meaningfully assign a probability to a prediction based on an analogical reasoning.

1 properties between source and target, but also the nature of the relation between these
2 properties:

3 „Under what circumstances can we argue from, for example, the presence of human
4 beings on the earth to their presence on the moon? The validity of such an argument
5 will depend, first, on the extent of the positive analogy compared with the negative
6 (for example, it is stronger for Venus than for the moon, since Venus is more similar
7 to the earth) and, second, on the relation between the new property and the properties
8 already known to be parts of the positive or negative analogy, respectively. If we have
9 reason to think that the properties in the positive analogy are causally related, in a
10 favorable sense, to the presence of humans on the earth, the argument will be strong.
11 If, on the other hand, the properties of the moon which are parts of the negative
12 analogy tend causally to prevent the presence of humans on the moon the argument
13 will be weak or invalid.“ (Hesse 1966, 58-59; cited in Norton 2011, 8)

14 In other words, Hesse proposes a two-dimensional model, where the horizontal relations
15 concern the similarity between source and target, i.e. the identity or difference in properties,
16 and the vertical relations concern the relations between properties, which Hesse believes to be
17 causal in most cases. Simply comparing the negative and the positive analogy thus will not
18 do, but rather the nature of the relationship between the properties in the positive and the
19 negative analogy with the properties in the hypothetical analogy has to be taken into account.

20 In his recent influential work on analogical reasoning, Paul Bartha very much builds on
21 Hesse’s two-dimensional account (Bartha 2010, briefly summarized in 2013, Section 3.5.2).
22 He classifies different types of analogical reasoning in terms of different vertical relations,
23 e.g. logical, causal, or statistical. Bartha’s *principle of prior association* then demands that
24 some kind of connection between the positive analogy and the hypothetical analogy has to be
25 established, taking into account the negative analogy as well. Bartha’s second principle, the
26 *principle of potential for generalization*, requires that there should be reason to expect that the
27 relationship between positive and hypothetical analogy in the source obtains for the target as
28 well. In particular, there should be no “critical disanalogy” between source and target.

29 Let me emphasize again that these modern authors have established that any reasonable
30 approach to analogy has to take into account both similarity in properties between source and
31 target as well as the relations between these properties and the hypothetical analogy. The
32 proposal in this essay builds on this important idea, a more detailed critique of both Hesse and
33 Bartha unfortunately is beyond the scope of this paper.

34

35 **3. Predictive and conceptual analogies**

36 In the following, I introduce a distinction between predictive and conceptual analogies, which
37 differ in various respects: concerning the epistemic aim, the nature of the vertical relations,
38 the criteria of evaluation, and the methodological framework.⁷ Arguably, the failure to clearly

⁷ The proposal is embedded within a broader distinction between phenomenological science on the one hand and abstract or theoretical science on the other hand. Perhaps the most important difference between

1 hold these types of analogical reasoning apart has led to considerable confusion in the debate
 2 on analogical reasoning. Maybe most importantly, only for conceptual analogies the role of
 3 analogical reasoning is primarily heuristic, while predictive analogies aim at true or at least
 4 probable inferences. As argued in section 2b, when discussing Keynes' approach, the latter
 5 type of analogies constitutes the core of inductive and causal reasoning.

6 An example of a predictive analogy is the use of animal models such as the mouse model in
 7 pharmacology to determine the effectiveness of certain medication to cure diseases in human
 8 beings. But as will become clear in the course of this paper and as was already emphasized by
 9 Keynes, any inductive inference from one instance to another instance, when aiming at truth
 10 or at least probability, can be construed as a predictive analogy. Further examples to be
 11 discussed in Section 4e concern predictions of the period of a pendulum or inferences to life
 12 on other planets.

13 Predictive analogies aim to establish reliable prediction or effective intervention.
 14 Consequently, the relevant vertical relationships must be of causal nature. This follows from a
 15 view of causation in the sciences as the crucial concept to distinguish between effective and
 16 ineffective strategies—as developed by Nancy Cartwright and others (especially Cartwright
 17 1979). Only if there is some causal link between administering the medication and recovery
 18 both in the mouse and in the human being, the analogical inference is reliable.

19 More exactly, a strategy how to effectively intervene in a phenomenon has to be based on a
 20 direct causal relationship between some circumstances in the positive analogy and the
 21 hypothetical analogy. Similarly, a reliable prediction must be based on some causal
 22 connection, which however need not consist in a direct causal link, but can also result from a
 23 common cause structure. In particular, an analogical inference aiming at prediction may infer
 24 from a correlation between two variables with a common cause in the source phenomenon to
 25 a similar correlation in the target phenomenon. By contrast, a merely accidental correlation
 26 that does not result from some causal connection cannot be used either for prediction or for
 27 intervention.

28 One might worry that the above argument presupposes Reichenbach's principle of common
 29 cause (1956, 157–159), which is controversial (e.g. Sober 1988). Colloquially, this principle
 30 can be formulated as follows: 'If there is a correlation between two events, then this
 31 correlation must be either due to a direct causal connection between the correlated events or
 32 due to a common cause.'⁸ Clearly, in the above argument such a principle of common cause is

phenomenological and theoretical science concerns the aim: the former is mainly interested in reliable prediction and successful manipulation, the latter in the development of a conceptual and explanatory framework. Thus, predictive analogies fit well with phenomenological science, conceptual analogies fit well with theoretical science. There are a number of further characteristics that both distinctions share, for example whether the laws that are used are causal or not. Some of the claims in this section can only be understood from the perspective of this broader distinction between phenomenological and abstract science, for which unfortunately I cannot argue here due to lack of space. Notable scholars, who have made and argued for the distinction, include Duhem (1954) and Cartwright (1983).

⁸ This is a typical formulation (e.g. Sober 2001, 331). Reichenbach was somewhat more cautious: "the *principle of the common cause* [...] can be stated in the form: *If an improbable coincidence has occurred, there must exist a common cause.* [...] Chance coincidences, of course, are not impossible [...] The existence of a common cause is therefore [...] only probable. This probability is greatly increased if coincidences occur repeatedly." (1956, 157-158)

1 not assumed, since accidental correlations are possible, which by definition do not result from
 2 a common cause. Elliott Sober’s well-known example of a correlation between Venetian sea
 3 levels and British bread prices is a plausible candidate for an accidental correlation.

4 However, such an accidental correlation is not a *reliable* correlation and thus cannot be used
 5 for *reliable* prediction. Therefore, accidental correlations cannot support sound analogical
 6 arguments. A *reliable* correlation, as I understand it here, requires that some reason exists,
 7 why the correlation holds and continues to hold. Such a reason could be a direct causal link, a
 8 common cause, or a definitional or normative relationship between variables.⁹ For accidental
 9 correlations, more or less by definition, such a reason does not exist. Therefore these cannot
 10 be employed for *reliable* prediction, even though a prediction based on an accidental
 11 correlation may very well turn out to be true by chance. Definitional or normative
 12 relationships between variables hold by stipulation and therefore cannot ground predictive
 13 analogical inferences, which concern empirical relationships.

14 In summary, no matter whether they aim at effective intervention or at reliable prediction,
 15 predictive analogies always have to establish a causal relationship in the target phenomenon
 16 based on some knowledge about a corresponding causal relationship in the source
 17 phenomenon.

18 Predictive analogies are evaluated by verifying whether an intervention works, which is
 19 suggested by the analogy, or whether a prediction turns out to be true. After all, there is a
 20 matter of fact, whether a medication that cures a disease in a mouse will also lead to recovery
 21 in a human being afflicted by a similar disease. Of course, as this example demonstrates, such
 22 predictive analogies will in general not be deterministic, but statistical, i.e. they will only hold
 23 with a certain probability. Thus, methodological frameworks for predictive analogies try to
 24 determine the truth or at least probability for analogical inferences. Both Carnap’s and
 25 Keynes’ approaches to analogy, as delineated in the previous sections, are examples of such
 26 probabilistic frameworks for analogical reasoning—covering chiefly predictive analogies.

27 An example for a conceptual analogy is the analogy between the transfer of heat and
 28 interaction in electromagnetic phenomena as it was elaborated in great detail by William
 29 Thomson and James Maxwell towards the end of the 19th century—resulting in the modern
 30 particle-field theory of classical electrodynamics:

31 “The laws of the conduction of heat in uniform media appear at first sight among the
 32 most different in their physical relations from those relating to attractions. The
 33 quantities which enter into them are *temperature, flow of heat, conductivity*. The word
 34 *force* is foreign to the subject. Yet we find that the mathematical laws of the uniform
 35 motion of heat in homogeneous media are identical in form with those of attractions
 36 varying inversely as the square of the distances. We have only to substitute *source of*
 37 *heat* for *centre of attraction, flow of heat* for *accelerating effect of attraction* at any

⁹ Due to lack of space, we cannot address here certain interesting, but controversial cases, such as correlations due to indeterministic relationships, which arise for example in connection with the Bell Inequalities, or correlations due to conservation laws.

1 point, and *temperature* for *potential*, and the solution of a problem in attractions is
2 transformed into that of a problem in heat. [...]

3 It is by the use of analogies of this kind that I have attempted to bring before the mind,
4 in a convenient and manageable form, those mathematical ideas which are necessary
5 to the study of the phenomena of electricity.” (Maxwell 1855/56, 157)

6 As is clear from this quote, Maxwell’s aim in developing the analogy between heat and
7 electricity is not primarily prediction or intervention. Rather, Maxwell wants to develop a
8 conceptual framework for electromagnetic phenomena based on another framework that was
9 more familiar and much better developed at the time, namely the theory of heat. Such
10 reasoning facilitates transferring certain results and solutions from one field to the other.

11 Since the primary aim is neither prediction nor intervention, the relevant vertical relationships
12 in such conceptual analogies are in general not causal—arguing again with a Cartwrightian
13 concept of causation as sketched above. In the example of classical electrodynamics, there are
14 good reasons to assume that the considered relationships are to considerable extent
15 definitional or conventional. In particular, this perspective is in accordance with a standard
16 view on the nature of axioms and laws of fundamental scientific theories—interpreting these
17 as implicit definitions of basic theoretical terms. Certainly, it cannot be the place here to
18 defend this view, but typical arguments range from underdetermination of abstract theory to
19 the observation that the laws in fundamental theories are too abstract to have themselves
20 considerable empirical content. Only when supplemented by further assumptions, e.g. bridge
21 principles according to the classic syntactic view of scientific theories, do these laws acquire
22 empirical meaning. This observation alone might suffice to establish the non-causal nature of
23 the fundamental laws of abstract scientific theories.

24 Relatedly, conceptual analogies are evaluated by whether they play a fruitful role in
25 transferring established solutions and results from one field to another rather than in terms of
26 truth and probability. While in predictive analogies, one can verify whether an analogical
27 inference corresponds to a matter of fact, e.g. whether a prediction turns out true or not, this is
28 in general not possible for conceptual analogies. To verify, whether a Poisson equation for the
29 electric potential holds, when postulated in analogy to the Poisson equation for temperature in
30 the theory of heat, is certainly not as simple as verifying predictive analogies. One reason lies
31 in the considerable underdetermination of abstract conceptual frameworks. Indeed, Maxwell
32 stressed the underdetermination of classical electrodynamics insisting that there exists
33 considerable flexibility how to formulate the fundamental laws. For example, a choice
34 between action at a distance and field theory in electrodynamics remains possible (Pietsch
35 2012).

36 Thus, conceptual analogies are a creative endeavor. Whether they hold, is not so much a
37 matter of truth and probability but to considerable extent depends on the ingenuity of the
38 scientists—whether they are successful in mapping (part of) the fundamental structure from
39 one phenomenon to the other. Consequently, such analogies cannot be treated in terms of
40 probabilistic frameworks like those of Carnap or Keynes. Approaches to analogical reasoning
41 based on structure mapping, such as from the work of Dedre Gentner (1983), seem much

1 more adequate. Gentner's framework relies on a classification of various entities, attributes
2 and relations as well as a quite sophisticated set of inference rules. Analogies are evaluated
3 according to a *systematicity principle*, essentially that those analogies are more plausible that
4 result from a mapping of mutually connected higher order relations compared with those
5 mapping only isolated properties. Note that this main criterion of the structure mapping theory
6 can hardly be translated into probabilities and consequently, Gentner's theory, while well
7 suited for conceptual analogies, seems unable to serve as a framework for predictive
8 analogies. Rune Nyruup's pursuit worthiness account is another example of an approach
9 intended for conceptual analogies (2016).

10 From yet another perspective, a relatively sharp criterion to distinguish between predictive
11 and conceptual analogies concerns a difference in epistemic attitude when formulating
12 analogies. In the case of predictive analogies, one is primarily interested in whether the
13 respective inferences turn out true or not. By contrast in the case of conceptual analogies, one
14 is prepared to engage in considerable conceptual reevaluation trying to reframe and redefine
15 relevant notions in order to make the analogy work. A conceptual analogy, thus, is never a
16 simple prediction but rather presupposes a substantial willingness of the scientist to try to
17 make the analogy fit the facts.

18 To some extent, conceptual analogies also aim at truth in that the conceptual framework,
19 which is developed on the basis of such analogies, is at some point used to make predictions
20 about the phenomena, for which the framework is intended. However, the primary focus is on
21 developing a simple, but fruitful conceptual basis with considerable explanatory power, while
22 the truth or probability of any predictions is only an indirect or secondary aim. In particular,
23 true or probable predictions based on the conceptual framework become important only at a
24 later stage, once the framework is sufficiently developed.

25 While the difference in attitude provides a relatively sharp criterion to distinguish between
26 predictive and conceptual analogies in scientific practice, one and the same analogy can still
27 be framed as either predictive or conceptual depending on the respective attitude of the person
28 formulating the analogy. For example, a scientist could use a mouse model to predict the
29 efficacy of a medication in humans, but could also use the same mouse model in order to
30 develop an understanding of how specific phenomena in the human body work.

31 Predictive and conceptual analogies are the main types of analogical reasoning in the
32 empirical sciences. Whether there are other types, for example in mathematics, is a difficult
33 question. Given the non-empirical nature of mathematics, predictive analogical inferences in
34 the above sense will not play a role in this field. With respect to conceptual analogical
35 reasoning, some variant is likely to be used in mathematics, not least in view of the substantial
36 similarities between mathematics and theoretical physics. Whether other types of analogical
37 inferences are employed, ultimately depends on the epistemological status that is attributed to
38 mathematics. However, that question leads us far away from the actual topic of the essay (see
39 e.g. Bartha 2010, Ch. 5).

40

1 **4. A deterministic framework for predictive analogies**

2 *4a. A first suggestion*

3 There exists a core intuition about valid analogical reasoning that can be found across the
4 literature and that is in line with the two-dimensional model sketched in Section 2c. This
5 intuition is for example incorporated in Bartha's second principle that for valid analogical
6 inferences no essential disanalogy between source and target should exist. The basic idea is
7 the following (PA):

8 A (predictive) analogical inference holds, i.e. the hypothetical analogy is true for the
9 target,¹⁰ if and only if the negative analogy concerns only *causally irrelevant*
10 circumstances.

11 Note that in line with the distinction introduced in Section 3, the vertical relations of interest
12 are causal in nature since the focus lies on predictive inferences. To repeat, this insight stems
13 from a Cartwrightian understanding of causation, the core feature of which is to draw a
14 distinction between effective and ineffective strategies, including between reliable and
15 unreliable prediction.

16 I will in the following suggest a methodology for predictive analogical inferences that builds
17 on the core intuition (PA). Before discussing the crucial notion of causal irrelevance, let me
18 briefly point out some possible objections against the proposed approach which are then
19 mostly addressed later on in order to refine (PA). A first issue concerns situations, where an
20 analogical inference is valid even though some circumstances in the negative analogy are
21 causally relevant—i.e. (PA) is not a necessary condition for predictive analogical inferences.¹¹
22 Notably a factor may be causally relevant, but may play no role in the considered analogy,
23 because other contributing factors are not instantiated, e.g. the burning match does not cause a
24 fire since there is no combustible material present. Also, the influences of some causally
25 relevant circumstances could exactly cancel each other. For example, one might infer from the
26 acceleration that a stone receives on the earth to the acceleration that a stone of the same mass
27 receives on the moon. The acceleration is indeed the same, if the difference in gravitational
28 field is exactly compensated by an acceleration of the system of reference on the moon.
29 Similarly, the same effect can be due to alternative causes, e.g. the acceleration of a body may
30 be caused by gravitational or by electromagnetic fields. An analogical inference may still be
31 valid even if in various instances different alternative causes are active, if the effects of these
32 different causes add up to the same result.

¹⁰ One might object that the validity of an analogical inference should not be confused with whether a prediction turns out true or not. Notably, it has been argued that valid inferences are those that adhere to commonly accepted methodological conventions, largely independently of empirical success. However, in the case of (predictive) analogical inferences, a necessary and sufficient criterion for empirical success can be stated. Under these circumstances, it seems adequate to identify valid (predictive) analogical inferences with those that obey the criterion.

¹¹ In this category falls a well-known example concerning the inference that there is life on Mars based on the existence of life on Earth, even though there apparently are relevant differences between both planets. How to deal with such examples will be outlined in Section 4c.

1 Secondly, certain cases suggest that (PA) is not a sufficient condition for predictive analogical
2 inferences. In particular, predictive analogical inferences may sometimes be based on
3 relationships other than causal relevance, e.g. on mere correlations. More exactly, even if the
4 negative analogy is causally irrelevant, the analogical inference could nevertheless fail to hold
5 due to mere correlations between some circumstances in the negative analogy and the
6 hypothetical analogy. To use a well-known example, one might infer that the bread price in
7 London this year will be the same as the bread price in London last year because the negative
8 analogy is causally irrelevant. However, upon reading an essay by Elliott Sober (2001), one
9 discovers that there exists a strong correlation between London bread prices and Venetian sea
10 levels. In addition, there are clear indications that the sea level in Venice this year is much
11 higher than last year. This seems to provide substantial evidence to infer that the analogy fails,
12 i.e. bread prices in London will not remain the same. Even though Venetian sea levels
13 presumably are causally irrelevant to London bread prices, a change in the former may
14 suggest a change in the latter due to the mentioned non-causal correlation—contradicting the
15 claim that only causally relevant circumstances are important for analogical inferences.

16 Relatedly, predictions are sometimes based on definitional relations. This can again result in
17 situations where analogical inferences fail to hold even though the causal structure has not
18 changed. For example, an analogical inference from the gravitational field in one location to
19 another at the same distance from the earth could fail just because the concept of a
20 gravitational field is understood differently in both situations.

21 A third point concerns the distinction between properties (which are ‘one-place’) and relations
22 (which are ‘many-place’). While the Keynesian terminology of positive and negative analogy
23 suggests a focus on properties rather than relations, many scholars insist that analogy is less
24 about a supposedly superficial similarity in terms of common properties of source and target,
25 but rather about similarity in terms of relations. For example, in the analogy between heat and
26 electricity, the essential similarity is not between corresponding terms such as temperature
27 and electric potential or source of heat and charge. Rather it concerns relations between these
28 terms, e.g. that they obey a Poisson equation.

29 To resolve this issue, note first that relations always link properties with each other. Thus, it
30 would be wrong to think that one could exclusively focus on relations neglecting properties
31 altogether. The Poisson equation, for instance, relates temperature and sources of heat as well
32 as charges and electric potential. Furthermore, the proposed approach (PA) obviously takes
33 into account relationships as well, by examining the causal relevance or irrelevance of certain
34 properties for others.

35 It might still be questionable, whether complex analogies can be formulated in terms of
36 positive and negative analogies. After all, it does not appear straightforward how to compare
37 concepts like temperature and electric potential in terms of differences and similarities? In
38 response, it should be stressed that if shared relations exist one can always formulate shared
39 properties corresponding to these relations. For example, both temperature and electric
40 potential share the abstract property that they serve as potentials which by means of
41 corresponding forces lead to the distribution of certain quantities. By contrast, electric
42 potential and temperature differ in terms of the nature of the potential, in particular regarding

1 the quantity on which it acts, namely either charged matter or heat. In this manner, positive
2 and negative analogy can be distinguished. With sufficient ingenuity, this is always possible.

3 Fourth and last, there are substantial worries concerning the notion of causal irrelevance. For
4 example, it is far from certain, whether causal irrelevance can ever be established at all. After
5 all, a circumstance that is normally considered irrelevant may suddenly become causally
6 relevant in some obscure situation. The constellation of the stars at birth is usually not
7 considered relevant to the fate of a person, but in some contrived story it might have an
8 impact. For example, the person may be superstitious and the astrological prediction of a
9 psychic may be so scaring that it becomes a self-fulfilling prophecy. The ultimate lesson to
10 draw from such counterexamples is that causal irrelevance is context-dependent and that in an
11 explication of analogical reasoning this must be taken into account. Such context-dependence
12 is of course not surprising to anyone familiar with the philosophical debate on causation. It
13 was stressed in particular by John Mackie, who in his approach to causation introduced the
14 crucial notion of a causal field, to which all causal statements are relative (1980).

15 Whether the basic intuition (PA) has merits or not, crucially depends on the construal of the
16 notion of causal irrelevance. To this issue we will turn now.

17 *4b. The notion of causal irrelevance*

18 In the following, I discuss several suggestions from the literature how to define causal
19 irrelevance and based on these will later lay out my own proposal. All in all, it seems fair to
20 say that the notion of causal irrelevance has not played a central role especially in
21 philosophical accounts of causation, which are almost exclusively focused on the notion of
22 cause in a positive sense, i.e. on causal relevance. Therefore, the following overview can be
23 rather brief.

24 First, one might try to define causal irrelevance based on statistical independence.¹² The most
25 straightforward connection between both notions originates within a probabilistic approach to
26 causation (see e.g. Hitchcock 2016 for a useful overview). If, broadly speaking, causal
27 relevance of an event C to another event E is identified with the increase or decrease of the
28 conditional probability $P(E|C) \leq P(E|\neg C)$, it seems natural to define causal irrelevance of C to
29 E in terms of an unchanged probability $P(E|C) = P(E|\neg C)$. As mentioned, most accounts of
30 probabilistic causation do not explicitly address the notion of causal irrelevance in much
31 detail. A notable exception in this regard is Ellery Eells who distinguishes positive, negative,
32 mixed, and neutral causal relevance—the latter corresponding to causal irrelevance (Eells
33 1991).

34 One important problem for a definition of causal relevance and irrelevance along these lines
35 are common cause structures, where a correlation between two variables F and G does not
36 result from a direct causal link between them, but rather from a common cause H that is
37 causally relevant to both variables. Let us assume in the following for reasons of simplicity
38 that all variables are binary. Even though no direct causal relevance between the variables F
39 and G exists, the conditional probability changes, e.g. $P(G|F) \neq P(G|\neg F)$. However, it is well

¹² While I will eventually seek a deterministic notion of causal irrelevance, it is nevertheless helpful to first also look at related suggestions, including statistical notions.

1 known that common causes shield off such correlations—i.e. while $P(G|F) \neq P(G|\neg F)$, we
 2 have $P(G|F\&H) = P(G|\neg F\&H)$ when conditionalising on H. Thus, one needs to control for
 3 common causes in order to identify the true relations of causal relevance or irrelevance.

4 For his definition of causal irrelevance, Eells suggests considering the probabilistic impact of
 5 a potential cause X on a potential effect Y in various causal background contexts. In each
 6 causal background context, all factors F_1, \dots, F_n that are causally relevant to Y, independently
 7 of X¹³, are held fixed. Only if the probability of Y is not changed by X in *all possible*
 8 contexts, should one speak of causal irrelevance (Eells 1991, 86). This condition is often
 9 called *contextual unanimity*. Note that Eells' definition of causal irrelevance is circular to
 10 some extent since the definiens itself employs the notion of causal relevance in that it requires
 11 all causally relevant factors to be held fixed in causal background contexts. However, he
 12 argues that the circularity is not vicious, since the definiens refers to the causal relevance of
 13 factors other than X, of which the irrelevance is examined (87). Eells further relativizes causal
 14 relevance and irrelevance to “a particular population, as well as to a kind that the token
 15 population exemplifies” (87). In part, this is required in order for a probability distribution to
 16 exist at all. Certainly, causal and probabilistic dependencies will differ between populations
 17 and kinds of populations.

18 The definition of causal irrelevance (CI) proposed below in Section 4c is in many ways
 19 similar to Eells's approach, but it is deterministic and introduces context-dependence in a
 20 somewhat different manner. Broadly speaking, context-dependence becomes simpler, since in
 21 a deterministic situation the existence of a probability distribution does not have to be
 22 ensured. As should be obvious, these changes with respect to Eells's account are necessary for
 23 correctly interpreting the role of causal irrelevance in (PA).

24 In recent years, a link between causality and probabilistic independence has been elaborated
 25 in the context of causal modeling on the basis of directed acyclic graphs satisfying the causal
 26 Markov condition—such graphs are often referred to as causal Bayes nets. The causal Markov
 27 condition implies a range of probabilistic independency relations. In particular, the
 28 probabilities for all nodes must be probabilistically independent when conditionalising on all
 29 parents PT of the nodes in the graph:

$$30 \quad P(X_1, X_2, \dots, X_n) = \prod_i P(X_i | PT(X_i))$$

31 Conditions like faithfulness or minimality further restrict the range of possible causal models.
 32 Faithfulness, for example, states that both conditional and unconditional probabilistic
 33 independencies in a graph must follow from the causal Markov condition. In particular, if two
 34 variables are probabilistically independent there should be no causal link between them.

35 The faithfulness condition illustrates well the difficulties that arise when building causal
 36 models merely from statistical relationships. On the one hand, premises like faithfulness are
 37 indispensable to reduce the number of possible models to a manageable amount. On the other
 38 hand, a range of counterexamples shows that faithfulness and related conditions can be little

¹³ i.e. factors that are causally relevant to Y but to which X is not causally relevant—excluding in particular factors that lie on a causal chain from X to Y.

1 more than pragmatic and fallible tools to develop causal models. As an example, the
2 faithfulness condition cannot account for causal relationships that exactly cancel each other.

3 Generally speaking, statistical independence is neither a sufficient nor a necessary criterion
4 for causal irrelevance. As mentioned, when causal influences between two variables exactly
5 cancel each other, there is presumably a causal link between these variables even though they
6 are probabilistically independent. Also, two variables may be probabilistically independent,
7 but in a number of instances of measure zero, there may nevertheless be causal relevance.
8 Such cases show that probabilistic independence is not sufficient for causal irrelevance. But
9 probabilistic independence is not necessary either. After all, as is elaborated in the following,
10 there are methods that determine causal irrelevance in deterministic situations, i.e. in
11 situations in which evidence in terms of probabilistic independence may be entirely absent,
12 for example because the relevant probability distributions are not even defined. Furthermore,
13 probabilistic independence can never be fully established empirically as fluctuations will
14 always lead to some small dependence.

15 As a second approach, let us take a look at deterministic definitions of causal relevance, i.e.
16 definitions that do not refer to probability distributions. A typical version is given by
17 Christopher Hitchcock:

18 “X is *causally relevant* to Y, if and only if there is some set of variables, and some set
19 of values of those variables, such that when we intervene to set all those variables to
20 those values, at least some interventions on the value of X will lead to different values
21 of Y.” (2009, 305)

22 In a similar vein, Michael Baumgartner and Gerd Grasshoff, who advocate a sophisticated
23 regularity view of causation, suggest:

24 „Factor A is causally relevant for the occurrence of an effect B, if and only if there
25 exists at least one causal process, in which an event of type A (partly) causes the
26 occurrence of an event of type B.“ (Baumgartner & Grasshoff 2004, 49; my
27 translation)

28 While most authors discussing causal relevance do not bother to explicitly define causal
29 irrelevance, it can be construed as complementary to causal relevance. Starting from the
30 above definitions, causal irrelevance would essentially require that *no* intervention can lead to
31 a change in values of the effect variable or that *no* process exists where an event of type A at
32 least partly causes the occurrence of an event of type B.

33 Such an approach to define causal irrelevance turns out inadequate for an analysis of
34 analogical inferences based on intuition (PA). After all, it may well happen that a
35 circumstance is causally relevant in some situation, while for the considered analogical
36 inference it plays no role, for example because other contributing causal factors are missing or
37 because there is a counteracting cause (cf. the first objection in Section 4a). Thus,
38 circumstances that are causally relevant according to the above definitions may change from
39 source to target, while the analogical inference may still be valid—contradicting (PA).

1 Indeed, very few circumstances will turn out causally irrelevant according to the above
 2 definitions, because in some obscure situation these might all be causally relevant (cp. the
 3 fourth objection in Section 4a). For this very reason, Baumgartner and Grasshoff largely reject
 4 the notion of causal irrelevance (2004, 212). One main lesson to draw from these attempts to
 5 define causal irrelevance is that context-dependence is not taken into account in an adequate
 6 manner. Exceptions to causal irrelevance in more or less obscure situations should be
 7 discounted on the basis that they occur within a context that differs from the one that is
 8 employed in the analogical inference.

9 David Galles and Judea Pearl belong to the small number of authors, who in an influential
 10 article (1997) explicitly define deterministic causal irrelevance and carefully implement
 11 context dependence:

12 “A variable X is causally irrelevant to Y , given Z [...] if, for every set W disjoint of X
 13 $\cup Y \cup Z$, we have

$$\forall(u, z, x, x', w), \quad Y_{xzw}(u) = Y_{x'zw}(u)$$

14 where x and x' are two distinct values of X .” (reproduced in Pearl 2000, 235-6)

15 Here, u are the values of the background or exogenous variables of the model. According to
 16 Pearl, this definition captures the intuition that “if X is causally irrelevant to Y , then X cannot
 17 affect Y under any circumstance u or under any modification of the model that includes
 18 $\text{do}(Z=z)$.” (Pearl, 236)

19 It may be possible to use this definition for an approach to predictive analogies based on (PA).
 20 However, this would turn out unnecessarily complicated. The first reason concerns model
 21 dependence. Galles and Pearl relativize their definition to a specific causal model that is
 22 determined by a number of exogenous or background variables U , a number of endogenous
 23 variables, and functions that determine each endogenous variable based on the other variables.
 24 The type of background dependence to be sketched in Section 4c is much simpler than such
 25 rather sophisticated model dependence. Secondly, by relying on an interventionist account of
 26 causation, Galles and Pearl subscribe to a substantial distinction between interventions and
 27 observations, which leads them to introduce the do-calculus for formally handling
 28 interventions. However, the notion of intervention plays no major role in analogical
 29 reasoning, neither in predictive nor in conceptual analogies, which suggests that an
 30 interventionist framework might not be the first choice for explicating analogy.¹⁴

31 Note finally that while (PA) suggests looking for a deterministic explication of causal
 32 irrelevance, this raises the question how to deal with indeterministic contexts and with
 33 situations, in which the evidence allows to formulate only probabilistic dependencies—an
 34 issue that will be briefly addressed in Section 5.

¹⁴ I have emphasized repeatedly Cartwright’s point that causation allows for implementing effective strategies. Note that this does not necessarily imply an interventionist take on causation. Instead, I favor an understanding in terms of difference making. The latter is more general and implies less ontological commitments compared with the interventionist approach.

1 *4c. A necessary and sufficient criterion*

2 Let me in the following sketch an account of causal irrelevance based on difference-making in
3 context. While we cannot ultimately defend the proposed definitions here, they should get
4 some initial plausibility from their close resemblance to the method of difference, which is
5 arguably the most successful rule in scientific method to determine causal dependence.¹⁵

6 Causal relevance shall be defined in the following manner (CR):

7 *A is causally relevant to C in a context B, if and only if (i) an instance exists, where A*
8 *and C occur in the context B, (ii) a second instance exists, where neither A nor C*
9 *occur in the same context B, and (iii) B guarantees homogeneity.*

10 Note again that this definition largely corresponds to the method of difference as given in
11 particular by John Stuart Mill. Note further that causal relevance of A to C with respect to B
12 implies that a change in A within a context B *always* leads to a change of C—in contrast to
13 the definitions by Hitchcock as well as Baumgartner and Grasshoff given in the previous
14 section. Causal irrelevance can then be defined as the complementary¹⁶ notion (CI):

15 *A is causally irrelevant to C in a context B, if and only if (i) an instance exists, where*
16 *A and C occur in context B, (ii) a second instance exists, where A does not but C still*
17 *occurs in the same context B, and (iii) B guarantees homogeneity.*

18 Causal irrelevance of A to C with respect to B implies that a change in A within context B
19 *never* leads to a change in C. For example, a switch is causally irrelevant to a light given two
20 instances, one, in which both switch and light are on, and another, in which the switch is off
21 but the light still on, while nothing else that could be relevant to the light has changed—the
22 last premise essentially corresponding to homogeneity. By contrast, the switch is causally
23 relevant, if in the second instance, the light is off.^{17,18}

24 The context or background B is constituted on the one hand by a set of circumstances that are
25 allowed to change and on the other hand by a set of circumstances that must remain constant.
26 Homogeneity, which was already invoked by Mill in his formulation of the method of
27 difference, essentially captures the intuition that factors in the background that are causally
28 relevant to the examined phenomenon may not change. It is a concept that is used both in
29 counterfactual approaches to causation such as by Rubin and Holland (e.g. Holland 1986) and

¹⁵ For a more extensive argument in favor of the proposed framework, compare Pietsch (2016).

¹⁶ As in Eells's approach, there are mixed cases, in which a circumstance is neither relevant nor irrelevant with respect to a given context.

¹⁷ Note that the definition has some seemingly counterintuitive implications. If, for example, a light is controlled by two switches A and A*, where the light is on if at least one of the switches is on, and if it is presupposed as part of the background conditions that A* is on, then A will be classified as causally irrelevant according to the definition (CI). While this sounds counterintuitive, the definitions above are intended as refinements or improvements of our everyday notions in order to make causal language more precise and avoid contradictions. Eventually, these seemingly counterintuitive implications will allow to resolve the first group of problems for (PA) as discussed in Section 4a.

¹⁸ Building on the example of footnote 16, A is causally relevant to C, if it is part of the background conditions that A* is always off, while A is causally irrelevant to C, if it is part of the background conditions that A* is always on. Again, this seeming contradiction only underlines the need to always relativize causal dependencies to a background.

1 also in sophisticated regularity approaches such as Baumgartner and Grasshoff (2004). The
2 latter provide an extensive discussion (2004, 208).

3 While homogeneity¹⁹ is usually defined that all causally *relevant* factors must *remain*
4 *constant*, I prefer the complementary perspective that only causally *irrelevant* circumstances
5 are *allowed to change*. In combination with the definitions discussed in the previous Section
6 4b, this has some subtle implications. Most importantly, the explication of homogeneity given
7 in the following is less demanding in that more circumstances are allowed to change. Notably,
8 some circumstances, e.g. causal factors that are only active in certain contexts, may be
9 identified as causally irrelevant based on (CI), while they are causally relevant according to
10 conventional definitions, such as those of Baumgartner and Grasshoff. Thus, these would
11 have to remain constant to ensure homogeneity according to Baumgartner and Grasshoff,
12 while they are allowed to change according to the following explication of homogeneity (H):

13 Context B guarantees homogeneity with respect to the relationship between A and C,
14 if and only if only circumstances that are causally irrelevant to C can change, (i)
15 except for A and (ii) except for circumstances that are causally relevant to C in virtue
16 of A being causally relevant to C.

17 The second exception allows for circumstances to change that lie on a causal chain through A
18 to C or that are effects of circumstances that lie on this causal chain.²⁰ Clearly, the above
19 explication implements the before-mentioned intuition behind the notion of homogeneity that
20 factors in the background B that are causally relevant to the examined phenomenon C may not
21 change.

22 Let me now briefly address how to deal with the problems that were raised in Section 4a.
23 Concerning the first objection, consider for example cases where two influences A and B
24 exactly cancel each other and therefore the analogical prediction remains valid even though
25 causally relevant circumstances change. In response, let me specify that for valid analogical
26 inferences it is not required that every property in the negative analogy *taken by itself* must be
27 causally irrelevant, but strictly speaking only all properties in the negative analogy *taken in*
28 *conjunction*. If A and B exactly compensate each other, then a change from $A \wedge B$ to $\neg A \wedge \neg B$
29 is irrelevant. Similarly, if A and B are alternative causes for a phenomenon C, then a change
30 from $A \wedge \neg B$ to $\neg A \wedge B$ is irrelevant for the phenomenon C. In the first case, A and B taken in
31 conjunction are causally irrelevant to C, as are $\neg A$ and $\neg B$. In the second case, A and $\neg B$
32 taken in conjunction are causally irrelevant to C, as are $\neg A$ and B.

33 In general, causal irrelevance of circumstances taken in conjunction can be defined in the
34 following way (CI’):

35 A number of factors A_1, A_2, \dots, A_N *taken in conjunction* is causally irrelevant to a
36 hypothetical analogy C with respect to a context B, if and only if (i) an instance exists,

¹⁹ Homogeneity broadly corresponds to context-unanimity in Eells’ account.

²⁰ The notion of ‘causal relevance in virtue of’ cannot be discussed here in further detail due to lack of space. An exact explication is: “A condition X is causally relevant to C in virtue of A being causally relevant to C with respect to a background B, iff in all contexts within B, in which X is causally relevant to C, A is causally relevant to C as well (but not necessarily vice versa).”

1 where A_1, A_2, \dots, A_N and C occur in context B , (ii) a second instance exists, where
 2 $\neg A_1, \neg A_2, \dots, \neg A_N$ and C occur in the same context B , and (iii) B guarantees
 3 homogeneity.

4 Thus, in order to determine causal irrelevance of a number of factors taken in conjunction,
 5 one does not need to test the causal irrelevance of each factor individually or the potentially
 6 huge number of all possible combinations of those factors. Instead, it suffices to establish the
 7 two situations mentioned above.²¹

8 Note further that if a factor which is commonly considered a cause fails to be relevant for the
 9 considered analogy because other contributing factors are not instantiated, e.g. the burning
 10 match does not cause a fire since there is no combustible material present, such a factor is
 11 identified as causally *irrelevant* with respect to the considered context according to the
 12 proposed definition (CI)—in contrast to all other definitions of causal irrelevance discussed in
 13 the previous section. Therefore, only the proposed definition of causal irrelevance (CI) in
 14 combination with the intuition (PA) correctly classifies such analogical inferences as valid. As
 15 an example, one might conclude from a barn without fire that another barn is not on fire either
 16 notwithstanding the presence of a burning match, just because combustible material is absent
 17 in the second barn.

18 The second problem raised in Section 4a concerned analogies based on correlations. Consider
 19 again the example that a circumstance F changes from source to target, which is causally
 20 irrelevant to the hypothetical analogy G , but which is correlated with it and therefore leads to
 21 the failure of the analogical inference. It turns out that such situations are precluded in the
 22 sketched approach. Indeed, according to the view of causation introduced in Section 3, any
 23 meaningful correlation between variables *must* result from a common cause, i.e. any
 24 correlation that leads to a *reliable* prediction. Therefore, in order for an analogical inference
 25 to fail in the described manner, the corresponding common cause variable must change.
 26 However, such a change in common cause variables is precluded by (PA), since these are not
 27 causally irrelevant to the hypothetical analogy.

28 In response to the problem that analogies may be based on definitional, instead of causal
 29 relevance, one might be tempted to restrict predictive analogies to causal vertical relationships
 30 only. However, this runs into problems with familiar epistemological issues such as
 31 confirmational holism and relatedly the lack of a clear distinction between empirical and
 32 definitional statements. Instead, I broadly suggest to integrate definitional relevance in the
 33 framework which should be rather easily done since definitional relevance can be defined in
 34 much the same manner as causal relevance—given that the main difference merely lies in the
 35 nature of the necessity between antecedent and consequent.²²

²¹ Requiring irrelevance for all possible combinations of variables or for each variable individually would be much too strong such that (PA') as stated below would not be a necessary criterion. For example, analogical inferences, in which two causally relevant factors exactly cancel each other, would be wrongly identified as invalid.

²² Basically, one needs to replace in (PA), (CI), (CR), and (H) “causally irrelevant” with “causally and definitionally irrelevant” as well as “causally relevant” with “causally or definitionally relevant”. Note that for predictive analogies, all changes in the definitions of relevant terms must be known in advance in order to clearly

1 With respect to the two other issues that were raised in Section 4a, the distinction between
 2 properties and relations was already discussed. Concerning the notion of irrelevance, (CI) in
 3 combination with (H) is supposed to yield an adequate explication. In particular, by
 4 introducing strict context-dependence, (CI) aims to avoid the problem that was pointed out in
 5 Section 4a, namely that causal irrelevance is practically inexistent, since any circumstance can
 6 be relevant in some obscure situation.

7 But a crucial question remains, namely what exactly should be chosen as an adequate context
 8 for the statement of irrelevance in the basic intuition (PA). Remember that a context consists
 9 of circumstances that are allowed to change and others that must remain constant. Since the
 10 impact of all circumstances that change (i.e. the negative analogy) is explicitly considered as
 11 antecedent, these cannot be ascribed to the context. What is left to account for are thus all
 12 circumstances that remain constant, i.e. the positive analogy. Apparently, these then constitute
 13 the context.

14 In summary, the proposed deterministic approach to predictive analogical inferences is given
 15 by the following explication (PA') in combination with the definitions of causal irrelevance
 16 (CI) and homogeneity (H):

17 Predictive analogical inferences from a source instance to a target instance are valid, if
 18 and only if the negative analogy (taken in conjunction) is causally (and definitionally)
 19 irrelevant to the hypothetical analogy with respect to a context constituted by the
 20 constancy of the positive analogy.

21 It is important to emphasize that in (PA') the negative analogy refers to the *complete* negative
 22 analogy, i.e. comprises all circumstances that differ between the source instance and the target
 23 instance. Similarly, the positive analogy refers to the *complete* positive analogy, i.e. all
 24 circumstances that are the same for source and target instance. In both cases, the considered
 25 circumstances thus include known as well as unknown circumstances. Furthermore, it is
 26 reasonable to restrict the considered circumstances to those in the past as well as in the
 27 present of the event denoted by the hypothetical analogy. Sub specie aeternitatis, one may
 28 need to also take into account circumstances in the future, but a discussion of this question is
 29 far beyond the scope of this paper.

30 Let me give an example to illustrate how (PA') is applied. Regarding the question, whether
 31 the existence of life on Earth allows inferring the existence of life on Mars, one would start
 32 from two instances or situations, the first (1) on Earth and the second (2) on Mars. Let us
 33 assume that it is known: (a) that the hypothetical analogy Q is true for (1), i.e. that life indeed
 34 exists on Earth; (b) what the positive and what the negative analogy between both situations
 35 is; (c) that the negative analogy taken in conjunction is irrelevant to the hypothetical analogy
 36 with respect to a background constituted by the positive analogy. Then, it can be concluded
 37 that the hypothetical analogy is true for situation (2), i.e. that life exists on Mars.

38 In a very simple illustration, it may be known that Earth and Mars differ only in temperature,
 39 which thus constitutes the negative analogy. Temperature is also the negative analogy taken in

distinguish predictive from conceptual analogies according to the criterion that only for conceptual analogies one is prepared to engage in conceptual work.

1 conjunction, since there is only one variable (cp. the definition in section 4b). All other
 2 variables constitute the positive analogy, by assumption these then have the same value for
 3 Earth and for Mars. Furthermore, one knows from some experiment relying on the method of
 4 difference that temperature is irrelevant to the existence of life, with respect to a context
 5 constituted by the positive analogy. For example, an ingenious scientist may succeed in
 6 briefly lowering the temperature on Earth to the temperature that is typically found on Mars,
 7 while at least some kind of life survives the temperature change. Carrying out the experiment
 8 on Earth ensures that the context is the same as in the examined analogical inference. Under
 9 these conditions, one can conclude from the existence of life on Earth to the existence of life
 10 on Mars.

11 *4d. Conceptual derivation*

12 (PA') can be reformulated in the following manner (PA''):

13 Given (i) a source instance $P \& N_1 \& \dots \& N_k$, of which it is known that C is the case,
 14 and (ii) a target instance $P \& \neg N_1 \& \dots \& \neg N_k$, of which it is not known whether C is
 15 the case, where P denotes the positive analogy, N_1, \dots, N_k the negative analogy and C
 16 the hypothetical analogy, the following holds:

17 if and only if (iii) $N_1 \& \dots \& N_k$ taken in conjunction is causally and definitionally
 18 irrelevant to C with respect to context P ,

19 then the analogical inference that C is the case for the target instance holds.

20 Note that for the sake of clarity and without loss of generality, all circumstances in the
 21 negative analogy are formulated in a positive way for the source instance and in a negative
 22 way for the target instance.

23 A proof of (PA'') proceeds as follows:

24 (I) To show that premise (iii) is a sufficient criterion, assume that (iii) is true.
 25 \Rightarrow It follows from the definition (CI') in combination with premise (i) of (PA') that
 26 the following instances exist: (1) $P \& N_1 \& \dots \& N_k \& C$ and (2) $P \& \neg N_1 \& \dots \&$
 27 $\neg N_k \& C$. Note that so far, instance (2) need not coincide with the target instance.
 28 \Rightarrow By definition, P denotes the *complete* positive analogy and $N_1 \& \dots \& N_k$ denotes
 29 the *complete* negative analogy with respect to the hypothetical analogy C .
 30 Therefore, in a deterministic setting, for which (PA'') is intended, the
 31 circumstances $P \& \neg N_1 \& \dots \& \neg N_k$ must uniquely determine, whether C is the
 32 case or not.
 33 \Rightarrow Therefore, since in the target instance the state of the circumstances $P \& \neg N_1 \& \dots$
 34 $\& \neg N_k$ is the same as in instance (2) and it is known that C is the case in instance
 35 (2), it follows that for the target instance the hypothetical analogy C must also be
 36 the case.
 37 \Rightarrow Thus, the analogical inference is correct.

38
 39 (II) To show that premise (iii) is a necessary criterion, assume that (iii) is false.

- 1 \Rightarrow It follows that one of the premises in (CI') must be false, i.e. one of the premises
 2 (a) that an instance $P \& N_1 \& \dots \& N_k \& C$ exists or (b) that an instance $P \& \neg N_1$
 3 $\& \dots \& \neg N_k \& C$ exists or (c) that the context P guarantees homogeneity.
 4 \Rightarrow By premise (i) of (PA''), an instance $P \& N_1 \& \dots \& N_k \& C$ exists. Also,
 5 homogeneity is trivially fulfilled, because the context consists only of
 6 circumstances P , which by assumption all remain constant. Thus, from premise
 7 (iii) of (PA'') being false follows that the remaining premise (b) of (CI') must be
 8 false, i.e. there may not be an instance $P \& \neg N_1 \& \dots \& \neg N_k \& C$.
 9 \Rightarrow According to premise (ii) of (PA''), there exists a target instance with the
 10 circumstances $P \& \neg N_1 \& \dots \& \neg N_k$. Furthermore, as explained under (I) above,
 11 the state of the circumstances $P \& \neg N_1 \& \dots \& \neg N_k$ must uniquely determine
 12 whether C is the case or not. Since an instance $P \& \neg N_1 \& \dots \& \neg N_k \& C$ may not
 13 exist, $\neg C$ must be the case for the target instance.
 14 \Rightarrow Thus, the analogical inference is false.

15
 16 From (I) and (II) follows (PA'') and therefore (PA').

17 *4e. Applicability*

18 In the following two sections, several points of criticisms with respect to the proposal of the
 19 previous section are discussed. In this first section, various issues concerning the applicability
 20 of (PA') are addressed. For example, one might doubt whether it is always possible to identify
 21 the positive and the negative analogy, even if sufficient evidence is available. In particular,
 22 one could object that analogical inferences are actually based on similarity, while such
 23 similarity cannot necessarily be spelled out in terms of a constant positive analogy and
 24 changes in a negative analogy.

25 As an example, consider again the question, whether the existence of life on Mars can be
 26 inferred from the existence of life on Earth. For instance, both Earth and Mars have an
 27 atmosphere, but it is not at all clear, whether having an atmosphere belongs to the positive or
 28 the negative analogy. After all, both planets have an atmosphere, but it also differs in
 29 important respects. Is it only possible to state a similarity between Earth and Mars with
 30 respect to having an atmosphere, while this similarity cannot be made explicit in terms of
 31 differences and conformities? In the end, the problem is that the chosen description is
 32 inadequate for the question at hand, because it is too coarse. Using sufficiently detailed
 33 terminology can resolve the issue. For example, the positive analogy might be that both
 34 planets have an atmosphere containing oxygen and carbon dioxide, while the negative
 35 analogy is that the concentrations of these components differ and that the atmosphere on Mars
 36 or Earth may contain traces of other gases, which are not present in the atmosphere of the
 37 other planet.

38 While differentiating the negative and the positive analogy will often be challenging, I do not
 39 see any reason, why it should not be possible in principle, if sufficient evidence is available.
 40 The following procedure corroborates this claim. Start with a sufficiently detailed description
 41 of the first phenomenon. All characteristics that need to be changed, taken away or added in
 42 order to arrive at a sufficiently detailed description of the second phenomenon constitute the

1 negative analogy, while all properties that remain the same constitute the positive analogy. In
 2 summary, it is an implicit premise of the proposed approach that any statement of similarity
 3 can be broken down into a positive and a negative analogy, but there are reasons to believe
 4 this should always be possible, at least in principle.

5 One might also worry about *practical* applicability. Even if it is possible to always clearly
 6 differentiate the positive and negative analogies in principle, it may still be the case that in
 7 real-world situations there is rarely sufficient evidence to apply (PA'). As a first remark, let
 8 me point out that in practice we often have quite reliable intuitions that a large range of
 9 circumstances are irrelevant and which circumstances may potentially be relevant. To further
 10 assess the issue at hand, let me also recall the main insight drawn from the discussion of
 11 Keynes' approach in section 2b, which was that all inductive inferences are to some extent
 12 based on analogy.

13 Consider for example a physicist, who examines two pendulums in order to determine
 14 whether their periods are the same, i.e. the time for a complete cycle. For this purpose, the
 15 physicist consults the relevant formula, which tells her that at least for small amplitudes, the
 16 period depends only on the length of the pendulum and on the acceleration of gravity at the
 17 location of the pendulum. In other words, the formula tells the physicist which variables are
 18 relevant, so that she can examine whether those relevant variables have the same value for
 19 both pendulums (or whether their deviations mutually compensate each other). If the lengths
 20 of the pendulums are the same and they are located in places with the same acceleration of
 21 gravity, then one can infer by analogy relying on (PA') from the period of one pendulum that
 22 the period of the other pendulum must be the same.

23 Whenever an inference is made for a specific situation based on a phenomenological scientific
 24 law that is empirically well established, this inference can be construed according to the above
 25 pattern as an analogical inference with respect to some of the evidence that was used to
 26 establish that law. In particular, the relevant experiments and observations, which were used
 27 to establish the law, allow to determine which variables are causally relevant to the considered
 28 phenomenon, usually by some application of the method of difference or the method of
 29 concomitant variation. Also, the evidence will include instances for which the hypothetical
 30 analogy is identical or at least very similar compared with the specific instance, which is
 31 predicted. In this way, the application of a phenomenological law can be interpreted as an
 32 implicit analogical inference according to (PA') with respect to such instances in the relevant
 33 evidence. Note further that analogical inferences can be considered on different levels of
 34 coarse-graining. In the above-mentioned example, one might infer the explicit value of the
 35 period, merely a value range to which the period belongs or even only the fact that pendulums
 36 have a constant period for subsequent oscillations. This shows that applications of (PA') are
 37 quite wide-spread.

38 As a further worry regarding applicability, many inferences that are considered typical
 39 analogical inferences do not seem to be covered by (PA'). In particular, (PA') does not
 40 guarantee that C holds in just any situation where P holds, as should be obvious at least from
 41 the equivalent formulation (PA'') given above. For example, for a successful predictive
 42 analogical inference according to (PA''), two instances must exist: a source instance (1) P &

1 $N_1 \& \dots \& N_k \& C$ and a target instance (2) $P \& \neg N_1 \& \dots \& \neg N_k \& C$. However, (PA'') says
 2 nothing whether C is the case for instances (3) for which P holds and at least one of the $N_1,$
 3 \dots, N_k is true, while at least one of the N_1, \dots, N_k is false. However, inferences from instances
 4 (1) and (2) to instances (3) seem to be typical analogical inferences.

5 At first, this appears to render (PA'') and thus (PA') practically useless. However, (PA'') can
 6 be applied in the above-mentioned evidence situation if additional assumptions are made, in
 7 particular if one can somehow reduce the number of circumstances of which the irrelevance in
 8 conjunction needs to be determined, instead of looking at the complete negative analogy. For
 9 example, it suffices to look at a smaller number of circumstances, if it can somehow be
 10 established that this smaller number of circumstances fully determines the truth or falsity of
 11 C , irrespective of whether the other circumstances are true or false in all those combinations
 12 that are possible in a given context.

13 Based on this insight, (PA''') can be formulated as a further version which is more directly
 14 applicable to practical examples, but which provides only a sufficient criterion for a predictive
 15 analogical inference to hold:

16 Given (i) a source instance $P \& N_1 \& \dots \& N_k$, of which it is known that C is the case,
 17 and (ii) target instances $P \& \neg N_1 \& \dots \& \neg N_m$ with $m < k$, of which it is not known
 18 whether C is the case and for which the remaining circumstances N with indices $m+1,$
 19 \dots, k can take on arbitrary combinations of values within a given range, the following
 20 holds:

21 if (iii) $N_1 \& \dots \& N_m$ taken in conjunction is causally and definitionally irrelevant to C
 22 with respect to a context determined by the constancy of P and by the circumstances
 23 N_{m+1}, \dots, N_k being allowed to take on any combination of values within the given
 24 range,

25 then the analogical inference that C is the case for the target instances holds.

26 Obviously, for applying (PA'''), it suffices to know the state of the circumstances $P \& N_1 \&$
 27 $\dots \& N_m$ for the source instance, while with respect to the other circumstances it must only be
 28 guaranteed that they are within the given range. Strictly speaking, P is not the complete
 29 positive analogy and circumstances $N_1 \& \dots \& N_m$ are not the complete negative analogy.
 30 After all, when specific source and target instances are considered, the circumstances $N_{m+1},$
 31 \dots, N_k can but need not vary and may thus belong either to the negative or to the positive
 32 analogy. More exactly, the positive analogy between a specific source and a specific target
 33 instance consists of P and the respective circumstances N with indices $m+1, \dots, k$, which
 34 remain constant between both instances, and the negative analogy consists of the
 35 circumstances N_1, \dots, N_k as well as those circumstances N with indices $m+1, \dots, k$ which
 36 change.

37 An equivalent formulation of (PA''') somewhat similar to (PA') reads as follows:

38 An analogical inference from a source instance to a range of target instances holds, if a
 39 first part of all circumstances taken in conjunction is causally and definitionally
 40 irrelevant to the hypothetical analogy with respect to a context determined by the

1 constancy of a second part of all circumstances and possible variations of the
2 remaining circumstances within a given range.

3 Typically, (PA''') can be employed, if the fraction N_{m+1}, \dots, N_k of all circumstances is
4 causally related to C only by means of the circumstances N_1, \dots, N_m for the given range of
5 possible variations of N_{m+1}, \dots, N_k . This could be the case for example in the following
6 situations:

- 7 i) the circumstances N_1, \dots, N_m and C may be causally unrelated to the circumstances
8 N_{m+1}, \dots, N_k for the given range of possible variations, i.e. colloquially speaking the
9 two groups of circumstances belong to different 'patches' of the world;
10
11 ii) the circumstances N_{m+1}, \dots, N_k may be causally related to C only by means of
12 common causes of those circumstances and C, where the common causes can be
13 expressed in terms of the circumstances N_1, \dots, N_m ;
14
15 iii) the circumstances N_{m+1}, \dots, N_k may lie on causal chains from the circumstances $N_1,$
16 \dots, N_m or combinations thereof to C, i.e. they may either be mediating circumstances
17 between the circumstances N_1, \dots, N_m and C or they may be causes of C, which act on
18 C only by mediating circumstances N_1, \dots, N_m . Essentially, circumstances on causal
19 chains co-vary and therefore do not have to be considered individually.
20

21 Of course, for most applications, combinations of the above situations will be the case. While
22 these situations typically cannot be established with certainty, it is straightforward to show
23 that increasing variational evidence of the type championed by Bacon, Mill or Keynes can
24 continuously improve the reliability of such assumptions. Assumptions of the above type are
25 wide-spread in the sciences and epistemology, e.g. various locality assumptions familiar from
26 physics or from philosophical debates on causation.

27 Obviously, (PA''') solves the problem, how to approach those analogical inferences, in which
28 one infers from evidence in terms of instances such as (1) $P \& N_1 \& \dots \& N_k \& C$ and (2) $P \&$
29 $\neg N_1 \& \dots \& \neg N_k \& C$ to other instances (3) for which P holds and at least one of the $N_1, \dots,$
30 N_k is true, while at least one of the N_1, \dots, N_k is false. But note that from a logical perspective
31 (PA'') and thus also (PA') remain necessary and sufficient criteria for predictive analogical
32 inferences to hold.

33 To illustrate (PA''') with an example, let us return once more to the life on Mars analogy.
34 Suppose in a still very artificial version of the Mars analogy that two factors are known to
35 differ between Earth and Mars, namely warm temperature (N_1) and the presence of two small
36 moons (N_2). For Earth, we have $N_1 \& \neg N_2$ and life exists (C). In addition, an exoplanet Alpha
37 is known with $N_1 \& N_2$ and where life exists as well as a further exoplanet Beta with $\neg N_1 \&$
38 $\neg N_2$ and where life also exists. How can an analogical inference to life on Mars with $\neg N_1 \&$
39 N_2 be established based on this evidence?²³

²³ I am grateful to one of the referees for this example, which I have quite shamelessly copied almost verbatim from the report.

1 Clearly, neither (PA') nor (PA'') provide an adequate basis for such an analogical inference
 2 without any further assumptions. However, if homogeneity of context can be established for
 3 all four instances, i.e. essentially that all other circumstances that may vary between the
 4 instances are causally related to C only via N_1 and N_2 , and if some additional assumption
 5 about the circumstances N_1 and N_2 can be established, then the requirements of (PA'') can be
 6 met. For example, it may be possible to show that N_1 and C are causally unrelated to N_2 , i.e.
 7 these two groups of variables belong to different 'patches' of the world, e.g. because other
 8 causal evidence proves the irrelevance of the number of moons for the existence of life. Or it
 9 may be possible to show that N_1 and N_2 act only independently from each other on C, if they
 10 are causally related to C at all. Under this latter assumption, e.g. the instantial evidence of
 11 Earth and Alpha proves the irrelevance of N_2 for C and the instantial evidence of Beta can
 12 then be used to analogically infer the existence of life on Mars relying on (PA'').

13 In summary, while from a logical point of view (PA') constitutes a necessary and sufficient
 14 condition for predictive analogical inferences, the application of (PA') to actual phenomena
 15 generally requires an adequate modeling of the phenomena as well as a host of further
 16 assumptions, which can be corroborated by variational evidence but which in principle always
 17 remain fallible.

18 *4f. Further discussion*

19 A number of further objections that could be raised against (PA') are addressed in the
 20 following. A first worry concerns the epistemological status of the complete negative analogy
 21 (and similarly of the complete positive analogy). Since it is not plausible that all
 22 circumstances which differ between two instances can ever be fully known, (PA') may appear
 23 to be merely a *metaphysical* rule with little practical import.

24 However, (PA') including the notion of a complete negative analogy is intended primarily as
 25 a *logical* rule. Without committing to any particular view on the nature of logic, several
 26 similarities between (PA') and other logical inference rules can be pointed out. All of these
 27 may be debatable and would actually deserve a much more detailed discussion, for which
 28 unfortunately there is not enough space. One crucial characteristic underpinning the logical
 29 nature of (PA') is that (PA') can be considered as truth-preserving. As with other logical
 30 rules, when the conclusion of (PA') fails to be true, one can always put the blame on one of
 31 the assumptions of (PA') being false rather than putting the blame on (PA') itself. Note that
 32 truth preservation is generally held to be a characteristic of deductive logic, while analogical
 33 inferences form part of inductive logic. Inductive rules are often thought to allow only for
 34 relationships between assumptions and conclusion that are somewhat weaker than truth-
 35 preserving.

36 As a further point, logical concepts typically are not directly applicable to the phenomena as
 37 has been discussed in much detail for (PA') in the previous section. Instead, the phenomena
 38 first have to be modeled in adequate ways. This is largely due to the abstractness of most
 39 logical concepts, which in turn can be seen to enable their universality. However, if the
 40 phenomena are adequately modeled, abstract logical concepts can become immensely useful.
 41 As an example, syllogistic inferences are among the most potent inferences in deductive logic,

1 even though it remains unclear whether there are any true universal statements in many of
 2 those fields, where syllogistic inferences are successfully employed. Who knows, whether all
 3 men are indeed mortal. Similarly, (PA') refers to all different circumstances between two
 4 instances. Whether these can ever be completely known is at best doubtful. Thus, as was
 5 pointed out in the previous section, (PA') requires some further modeling assumptions, which
 6 reduce the number of differences to a manageable amount.

7 Stressing the logical nature of (PA') may somewhat alleviate the worry that the concept of a
 8 complete negative analogy is too open-ended. After all, this worry relates to the differences
 9 between actual instances in the world, while (PA') is primarily a rule in an abstract conceptual
 10 framework that aims for consistency and precision. In a way, (PA') may be considered as a
 11 vanishing or limiting point, which can never be fully reached but which can be approximated
 12 further and further by collecting the appropriate kind of evidence.

13 A second issue that is somewhat related to questions of applicability arises regarding the
 14 notion of causal irrelevance (CI). It may well be that strictly speaking, no circumstance fully
 15 satisfies (CI) and thus that no circumstance is truly irrelevant to a phenomenon.²⁴ Specifically,
 16 there might always be some however faint causal influence, by which the circumstance and
 17 the phenomenon are connected. It thus appears that (PA') can never be fulfilled, because the
 18 negative analogy is never entirely irrelevant to the phenomenon.

19 The conclusion to draw from this objection is that causal irrelevance is a contextual notion,
 20 which depends on the amount of coarse-graining that is assumed for the relevant variables. In
 21 the pendulum example of the previous section, an inference that the periods of two pendulums
 22 are *exactly* the same does not make much sense, since in the empirical sciences, any value can
 23 only be determined up to some degree of accuracy. While the negative analogy will
 24 presumably always be causally relevant to some extent, the crucial question is, whether the
 25 effect of this causal relevance is larger than the amount of coarse-graining that is assumed for
 26 the variables in the hypothetical analogy. If the deviation is small enough *for the purpose at*
 27 *hand*, the variables in questions must be considered causally irrelevant *for that purpose at*
 28 *hand*. Consequently, (PA') can still be considered to hold.

29 A third issue which is also related to the notion of causal irrelevance is that the definitions
 30 (CI') and (H) suffer from a circularity in that (CI') presupposes (H) and (H) presupposes
 31 (CI'). However, this objection can be overcome in a similar manner as proposed by Eells' for
 32 an analogous circularity arising in his account (cp. Section 4b). In particular, definition (H)
 33 refers to the causal irrelevance of other circumstances, namely circumstances of the context,
 34 than the circumstances, whose causal irrelevance is explicitly examined in (CI').

35 As a fourth criticism, many analogical inferences do not follow the rationale of (PA') by
 36 examining the causal irrelevance of the negative analogy, but are based on other kinds of
 37 evidence, for example on correlations, on statistical laws, on retrodictions, etc. Such
 38 analogical inferences often enough turn out valid and there are in many cases good reasons to
 39 be fairly confident in them. One may want to call *strong predictive analogical inferences*
 40 those that are based on evidence in terms of the causal irrelevance of the negative analogy,

²⁴ I am grateful to one of the referees for bringing up this issue.

1 while *weak predictive analogical inferences* are based on other types of evidence.²⁵ Strong
 2 analogical inferences are certain if sufficient evidence is available, while weak analogical
 3 inferences mostly convey only a degree of probability or even only plausibility. Strong
 4 analogical inferences are based on causal relationships and therefore imply knowledge about
 5 interventions, while this is not necessarily the case for weak analogical inferences.

6 From a fundamental epistemological perspective, any weak analogical inference, which
 7 proves reliable, must be based on a corresponding strong analogy, which underlies the weak
 8 inference but is at least partly unknown to the person drawing the inference. Thus, all types of
 9 evidence mentioned above in connection with weak analogical inferences are only useful to
 10 the extent that they indicate the existence of an underlying strong analogy. For example, an
 11 analogical inference based on correlations is only reliable, if the correlated variables are
 12 adequate proxies for underlying causal variables, e.g. in terms of common causes. In
 13 retrodictions, the future variables should be suitable proxies for past causal variables, which
 14 may for example be connected to the future variables by means of deterministic laws.

15 Finally, not all relevant variables may be known such that one has to rely on statistical causal
 16 relationships. The analogical inference will then be valid only with a certain probability. This
 17 case, which has considerable practical significance, will be briefly addressed in the next
 18 section 5.

19 According to a fifth point of criticism, (PA') presupposes determinism with respect to the
 20 variables of the hypothetical analogy, i.e. that those variables are fully causally determined by
 21 their respective circumstances. In the case of indeterminism, (PA') may be fulfilled, but the
 22 analogical inference may nevertheless fail to hold because pure chance interferes. One could
 23 of course alter (PA') such that it also accounts for indeterministic cases. Essentially, in
 24 indeterministic situations the analogical inference holds only *with the corresponding objective*
 25 *probability*. Furthermore, the status of the indeterministic hypothesis, i.e. the claim that the
 26 world is to some extent indeterministic, remains uncertain even with respect to microphysics,
 27 as supposedly deterministic interpretations of quantum mechanics show, in particular
 28 Bohmian mechanics. And even if the micro-realm is indeterministic, many macro phenomena
 29 are deterministic, e.g. those treated by much of classical physics and engineering, and thus
 30 (PA') in the deterministic version of the previous section applies to these phenomena.

31 A sixth issue concerns the so-called problem of induction. According to a wide-spread
 32 consensus in epistemology and philosophy of science, inductive inferences are always fallible.
 33 We can never know for certain, whether an empirical prediction based on an inductive
 34 inference will turn out true. Some tension seems to exist between this insight and the claim of
 35 the previous section that (PA') constitutes a necessary and sufficient criterion for the truth of
 36 predictive analogical inferences.

37 In this context, two assumptions should be distinguished. The first regards whether a
 38 consistent logic of induction exists. The second assumption regards whether we can ever be
 39 completely certain that the premises for a valid inductive inference are fulfilled, even if a

²⁵ I am grateful to one of the referees for suggesting this helpful distinction.

1 consistent inductive logic is available. The general fallibility of inductive inferences may
2 result from a failure of either the first or the second assumption.

3 While many scholars doubt the existence of an inductive logic, the first assumption is much
4 more controversial than the more general point that inductive inferences are in principle
5 fallible. Certainly, influential scholars have in the past attempted to formulate a consistent
6 inductive logic and seem to have believed that such a program is feasible at least in principle,
7 e.g. Carnap and Keynes (cp. Section 2a and 2b). Equally, in the essay at hand, I start from the
8 assumption that eliminative induction can provide a consistent framework of inductive logic,
9 into which (PA') can be embedded.

10 It is the failure of the second assumption that leads to the general fallibility of inductive
11 inferences. With respect to predictive analogical inferences, it turns out impossible to fully
12 verify empirically, whether all premises required for (PA') are fulfilled. Most importantly,
13 while we often have strong intuitions which circumstances may be relevant, it is impossible to
14 know with absolute certainty. After all, among the myriads of circumstances that change
15 between two instances, there may always be some circumstance, however far-fetched and
16 remote it may appear, that has not yet been taken into account, but which eventually might
17 turn out relevant. Thus, judgments of causal irrelevance are always fallible and consequently
18 inferences based on (PA').

19

20 **5. Analogy and probability**

21 Thus far, we have only addressed deterministic analogical inferences that hold with certainty.
22 Of course, analogical inferences are often only probabilistic: Given a certain known positive,
23 known negative and unknown analogy, what is the probability that the hypothetical analogy is
24 the case for the target phenomenon?

25 An extension of the approach delineated in Section 4c to cover such probabilistic inferences is
26 straightforward. Let me briefly discuss the most important cases: (i) first, there may be an
27 unknown analogy, which is causally relevant; (ii) second, there may be a negative analogy,
28 which is causally relevant only with a certain probability; (iii) there may be situations of
29 indeterminism.

30 Regarding the first case, we have thus far only considered ideal situations, in which every
31 circumstance is known to belong either to the positive or to the negative analogy. Now, as
32 Keynes has rightly pointed out, in actual situations it is usually unknown of a number of
33 circumstances whether they belong to the positive or negative analogy. Assume for the sake
34 of simplicity that the unknown analogy consists of only a single circumstance which is
35 causally relevant in the respective context. Then, the analogical inference is valid with the
36 probability that this circumstance belongs to the positive rather than the negative analogy, if
37 otherwise (PA') holds. Equally, if there is more than one factor in the unknown analogy, one
38 has to determine the combinations which are causally relevant and then add up the respective
39 probabilities belonging to those combinations.

1 In the second case, one may be uncertain whether circumstances that belong to the negative
 2 analogy are causally irrelevant. Thus, the analogical inference is valid with the probability
 3 that these circumstances taken in conjunction are causally (and definitionally) irrelevant.
 4 Finally, in cases of indeterminism, i.e. in cases where the circumstances determine the
 5 hypothetical analogy only up to a certain probability, analogical inferences are valid with that
 6 probability. Of course, in such situations, causal relevance has to be interpreted in a
 7 probabilistic manner determining a probability distribution over states and not the state itself.

8 These are the principal cases, how probabilities may enter the assessment of analogical
 9 inferences. Of course, various combinations are possible, for example there may be an
 10 unknown analogy of which it is unknown whether it is causally relevant. While one has to
 11 carefully keep track of the corresponding probabilities, these complications do not add any
 12 substantial conceptual problems.

13 At this point, one may worry again about applicability. But in line with the Keynesian insight
 14 that analogical reasoning is essential not only for deterministic, but in particular also for
 15 probabilistic inferences, it turns out that the framework delineated above underlies many
 16 forms of inductive reasoning in statistics and probability theory. For instance, whenever one
 17 infers from a representative sample to a new individual, the above framework is employed.
 18 Let us assume that the probability to get lung cancer is 30% in a representative sample of a
 19 given population, e.g. all smokers. From this, one concludes that a certain further individual,
 20 who belongs to the same population of smokers, will get lung cancer with a probability of
 21 30%. Essentially, the population is defined by the extent that certain factors are allowed to
 22 vary while others remain constant, e.g. genetic factors, living conditions, habits etc. These
 23 factors determine the positive and negative analogy between the various individuals of the
 24 population. Of these factors, it is often not known, whether they are present or absent in
 25 specific individuals and/or whether they are causally relevant to smoking. This is the reason
 26 why we rely on representative samples in the first place. Now, the 30% probability basically
 27 expresses that

- 28 • in average, combinations of factors which are relevant to lung cancer are present with
- 29 a probability of 30 % in each individual of the population or
- 30 • in average, combinations of factors which are present in the population are relevant to
- 31 lung cancer with a probability of 30%.

32 Basically, these correspond to the cases (i) and (ii) as introduced above. Thus, an inference to
 33 the probability for a new individual relies on the discussed framework, if we know that the
 34 individual belongs to the same population as a representative sample, for which the respective
 35 probability is known. Note finally that such probabilistic inferences are *predictive* analogical
 36 inferences as long as the person making them is not prepared to implement definitional
 37 changes.

38 One crucial question, however, which goes far beyond the present article, concerns the
 39 interpretation of probability in such probabilistic analogical inferences (cp. Pietsch 2015). On
 40 the one hand, the interpretation presumably needs to be objective as prediction and
 41 intervention concern matters of facts rather than subjective credence. On the other hand, the

1 most common objective interpretation, the frequentist approach, is not an adequate
 2 interpretation since it belongs to the tradition of what was called above enumerative
 3 approaches to induction, which are generally hostile to analogical reasoning.

4

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7

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