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THEORY ASSESSMENT AND COHERENCE

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Abstract
One of the most important questions in epistemology and the philosophy of science is: what is a good theory and when is a theory better than another theory, given some observational data? The coherentist's answer would be the following twofold conjecture: (*i*) A theory is a good theory given some observational data iff that theory coheres with the observational data and (*ii*) a theory is better than another theory given some observational data iff the first theory coheres more with the observational data than the second theory. In this paper we show that this answer is a good answer. More precisely, we argue that the coherence measures of Olsson (2002) and Shogenji (1999) are good measures for the purpose of comparing and evaluating theories, i.e. assessing theories. We do so by clarifying the sufficient and necessary conditions every assessment function must satisfy for being a good measure of the goodness of theories. Afterwards we will show that the coherence measures of Olsson and Shogenji are indeed good assessment functions for assessing theories.

1. Introduction

One of the most important questions in epistemology and the philosophy of science is: what is a good theory and when is a theory better than another theory, given some observational data? The coherentist's answer is the following twofold conjecture: (*i*) A theory is a good theory given some observational data iff that theory coheres with the observational data and (*ii*) a theory is better than another theory given some observational data iff the first theory coheres more with the observational data than the second theory. In this paper we show that this answer is a good answer. More precisely, we argue that the coherence measures of Olsson (2002) and Shogenji (1999) are good measures for the purpose of comparing and evaluating theories, i.e. assessing theories. We do so by clarifying the sufficient and necessary conditions every assessment function must satisfy for being a good measure of the goodness of theories in section one. More precisely, following Huber (2008) we require from an assessment function to favor true theories over false theories and to favor true and informative theories over true but uninformative theories. In the third section we will then focus on the relation between the coherence measures on the one hand and theory assessment on the other. We will show that the degree of coherence of a theory and the observational data depends on two epistemic virtues of theories: the probability of the theory given the observational data and the informativeness of the theory. In the concluding section four we will show that the coherence measures of Olsson and Shogenji are indeed good assessment functions for assessing theories.

2. What is a Good Measure for Assessing Theories?

The basic claim of this paper is: the coherence measures of Olsson (2002) and Shogenji (1999) are good measures for the purpose of comparing and evaluating theories, i.e. assessing theories. But what is a good measure for this purpose? The answer is as easy as it can be. A good measure for assessing theories is a measure that takes us to good theories. But what is a good theory? It is clear that, if we consider good theories to be simple theories, regardless whether they are true or false, then we need another measure for evaluating theories than if we consider true theories to be good theories (at least if we don't have any reasons to believe that simple theories are true theories). According to Huber (2008) a good theory should be both: true and informative. A good theory should be true, because we simply do not want to believe false theories. A good theory should be also informative because from a good theory we expect more than just its truth. A good theory also provides us with valuable information about how the world is, i.e. it is a theory that is at least not logically true. As already said we follow Huber (2008) by interpreting good theories as true informative theories. However, historically Popper was one of the first and most prominent philosophers who stressed that informative theories constitute one of the aims of science. He writes:

> *Science does not aim, primarily, at high probabilities. It aims at a high informative content, well backed by experience. But a hypothesis may be very probable simply because it tells us nothing, or very little.* A high degree of probability is therefore not an indication of 'goodness' – it may be merely a symptom of low informative content.[1]

Furthermore, we do not only want to know what theories are good theories, we also want know which theories are better than others. Hence, we also have to state the conditions under which one theory is better than another theory. Of course, our first requirement on good assessment functions is that they favor good theories, i.e. theories that are true and informative, over theories, which are not good, i.e. theories which are not true or which are not informative. The interesting question is how we should

[1] Popper (1968: 399)

compare theories which have the same truth-value. This is so because in that case it obviously cannot be their truth-value which accounts for that. But whereas two good theories must have the same truth-value they can differ with respect to the information provided by them. In some intuitive sense, a true theory gets better the more informative it is. So we have to answer the question: “*When is a theory more informative than another theory?*”

We have to distinguish between a narrow and a wide usage of the term ‘information.’ According to the narrow usage of the term, information is always true. According to the wide usage, information is not always true. Only in this wide usage of the term ‘information’ it is meaningful to speak of false information. In order to differentiate between both we will use the term ‘information’ in its narrow usage, and we will use the term ‘content’ instead of ‘information’ in its wide usage. The content of a theory is then the set of all sentences which are implied by the theory. The information provided by a theory is the set of all true sentences implied by that theory. From this specification of the terms ‘information’ and ‘content’ it should be clear that it is the information provided by a theory which represents an epistemic value. The content of a theory itself does not represent an epistemic value independent of the truth of the theory. It should also be noticed that if we consider true theories, then that theory is the more informative one which has the greater content.

Now let us discuss in more detail how we should measure the content of and the amount of information provided by theories. Fortunately here we can benefit from the work of other philosophers in this field. The first who developed a quantitative concept of the content of a sentence and the information provided by it were Carnap and Bar-Hillel. This work was done in their technical report Carnap/Bar-Hillel (1952). Hintikka puts the idea underlying their approach as follows:

> The basic idea of their [Carnap, Bar-Hillel] approach may be said to be one particular way of explicating the idea that information [in the wide usage of the word] equals elimination of uncertainty. In order to measure this uncertainty, a distinction is made between the different logical possibilities that we can express in a language. The more of them a statement *s* admits of, the more probable it is in some “purely logical” sense of probability. The more of them a statement *s* excludes, the less uncertainty it leaves, and the more informative will it therefore be. The probability *p*(*s*) and information *inf*(*s*) of a statement *s* are thus inversely related.[2]

[2] Hintikka (1999: 206)

The measure of content Carnap and Bar-Hillel worked out is the following.

Definition 2.1

$$cont_p(T)=p(\neg T)$$

This measure of the content of a sentence is highly plausible, since it satisfies a requirement, which we might very well want to impose on the relation between content and probability. This requirement is the following: if $cont(T_1)$-$cont(T_2)=r$, then $p(T_2)$-$p(T_1)=a\times r+b$ for some $a, b \in \boldsymbol{R}$. This requires, that if the content of a theory T_1 exceeds the content of a theory T_2 by r, then this should be reflected in the difference of the prior probabilities of the theories. A theory which has less content than another theory should not only be a priori more plausible, the difference in their a priori plausibility should also be a linear function of their difference in content. More precisely, the difference in their probability should be an inverse order and interval preserving function of their difference in content. In the light of this requirement the above definition is the natural choice, if we additionally require that $cont$: $\boldsymbol{L} \rightarrow [0, 1]$ and $cont(A\vee\neg A)=0$.

In the literature we can also find a relativized measure of information. Since the observational data describe that part of the world that we are already familiar with via observations, we could assign degrees of informativeness to a theory relative to the observational data. Instead of asking how much a theory informs about the world, we ask how much the theory informs about the observational data. The next measure was proposed in Huber (2008) to measure exactly this.

Definition 2.2

$$i_p(T,E)= p(\neg T|\neg E)$$

if $p(\neg E)>0$

This information measure has an even longer history, than the content measure. It was introduced by Hempel/Oppenheim six years before Carnap and Bar-Hillel wrote their technical report. In their paper *Aspects of Scientific Explanation* (1965) they presented it not as a measure of information, but as a "measure of the systematic power" of a theory. It was meant to measure the explanatory and predictive power (in the sense of Hempel-

Oppenheim) of a theory, given some data. Hilpinen (1970) suggested this measure for measuring how much the observational data inform about a theory (he of course used $p(\neg E|\neg T)$). He called it 'normalized common content measure'. See Hilpinen (1970) for a detailed axiomatic motivation of this information measure.

In the light of this discussion of the informational value of true theories we can now state what we expect a good measure for assessing theories to be.

For a given Language $\boldsymbol{L}$ a function $a: \boldsymbol{L} \rightarrow \boldsymbol{R}$ is a good assessment function in world w iff for all theories T_1, T_2 and every data stream $e_1, \ldots, e_n, \ldots$ from w (including all possible observational data of w) it holds that:

1. if T_1 is true in w and T_2 is false in w, then there exists a point n such that for all $m \geq n$ holds that:
$$a(T_1,E_m)>a(T_2,E_m)$$
2. if T_1 is true in w and T_2 is true in w and $cont(T_1)>cont(T_2)$, then there exists a point n such that for all $m \geq n$ holds that:
$$a(T_1,E_m)>a(T_2,E_m)$$

where $E_m=e_1 \wedge \ldots \wedge e_m$

The first condition rests on the idea that true theories are better than false theories. Therefore a good assessment function must assign a higher assessment value to true theories than to false theories, at least after finitely many steps of observations. The second condition demands from a good assessment function that theories with more content score higher than theories with less content, given both theories are true. This second condition rests on the intuition that if we would have to decide between two true theories, we would prefer the theory with more content. This is so, because such theories inform more about the world than theories with less content. These requirements that any assessment function must satisfy in order to be a good assessment function are more or less taken from Huber (2008). In fact the requirements stated here are in two aspects weaker than those which Huber (2008) states as requirements that any assessment function must satisfy for "revealing the true assessment structure in world w". First, our requirement on good assessment functions that true theories score higher than false theories after finitely many steps of observation is strengthened in Huber (2008). He additionally requires that there is a demarcation $\beta \in \boldsymbol{R}$ such that after finitely many steps of observation true theories score higher than β and false theories score lower than β. Second, Huber (2008) adds a third requirement on good assessment functions. He additionally requires that if both theories T_1 and T_2 are false in w and T_1 is logically stronger than T_2, then is T_1 preferable to T_2 and consequently an assessment function should assign to the logically stronger T_1 a higher assessment value than to T_2 after finitely many steps of observations. Presumably he does so because he thinks that the content of a theory represents an epistemic value in its own right. Since we do not subscribe to the point of view that the content of a theory represents per se an epistemic value, i.e. independent of the truth of the theory, we drop this requirement.

3. Probability, Informativeness, and Coherence

In the last section we have seen what properties a good assessment function exemplifies. A good assessment function favors true theories over false theories and it favors more informative true theories over less informative true theories. Since we want to argue that the coherence measures of Olsson and Shogenji are such good assessment functions we have to show that the degree of coherence of a theory and the available observational data depends somehow on the epistemic virtues of a theory, i.e. its probability with respect to the observational data on the one hand and its informativeness on the other. To accomplish this the coherence measures must somehow weigh between both aspects which render a theory good or better than another. That there is indeed a dependency between the degree of coherence of a theory and the observational data and the above mentioned content measure *cont* or the information measure *i* and the conditional probability of the theory given the observational data will be shown in the following subsections.

3.1 Probability, Informativeness, and Olsson's Measure of Coherence

The Olsson (2002) measure of coherence is defined as follows:

Definition 3.1

$$C_{O,p}(A_1,\ldots,A_n) = \frac{p(A_1 \wedge \ldots \wedge A_n)}{p(A_1 \vee \ldots \vee A_n)}$$

if $p(A_1 \wedge \ldots \wedge A_n) > 0$ and 0 otherwise.

According to Olsson (2002) this measure of coherence measures the degree of agreement of the sentences $A_1, \ldots, A_n$. But a far more obvious interpretation of Olsson's coherence measure is that it measures how much the beliefs expressed by $A_1, \ldots, A_n$ hang together. Here we understand 'hang together' in the following way. Beliefs hang together if they are either true together or false together. In other words, beliefs hang together if, under the assumption that at least one of the beliefs is true, all of them are true. Olsson's coherence measure fits this intuition perfectly. The degree of coherence of sentences $A_1, \ldots, A_n$ equals the conditional probability of all of them being true, given that at least one of them is true, i.e. their disjunction is true[3].

Now let us take a closer look at the connection between the Olsson (2002) measure of coherence, probability, and the above mentioned measures of content and information. From the definition of the Olsson (2002) coherence measure and the fact that $p(T\vee E) = 1\text{-}p(\neg T\wedge\neg\text{E})$ it is easy to obtain the following result:

Theorem 3.1

If $p(T_1|E) = p(T_2|E) > 0$, then:

$$C_{O,p}(T_1,E) > C_{O,p}(T_2,E) \text{ ™ } i_p(T_1,E) > i_p(T_2,E)$$

And we can also prove the following:

Theorem 3.2

If $i_p(T_1,E) = i_p(T_2,E)$, then:

$$C_{O,p}(T_1,E) > C_{O,p}(T_2,E) \text{ ™ } \mathrm{p}(T_1|E) > \mathrm{p}(T_2|E)$$

Theorem 3.1 shows that if the conditional probabilities of two theories T_1 and T_2 given E equal each other, then the degree of coherence of T_1 and E is higher than degree of coherence of T_2 and E iff T_1 informs more about the observational data E than T_2 (in the sense of i. This shows that the degree of coherence between a theory and the

[3] This is obvious since $|= (A_1\wedge\ldots\wedge A_n)\leftrightarrow(A_1\wedge\ldots\wedge A_n\wedge(A_1\vee\ldots\vee A_n))$. This implies that:
$\frac{p(A_1\wedge..\wedge A_n)}{p(A_1\vee...\vee A_n)} = \frac{p(A_1\wedge..\wedge A_n\wedge(A_1\vee...\vee A_n))}{p(A_1\vee...\vee A_n)}$. It is remarkable that our understanding of 'hanging together' is the same as that of Shogenji (1999). He writes: "The crudest way of unpacking the idea that coherent beliefs 'hang together' is that they are either true together or false together. However, coherence comes in degree; in other words we want to say that the more coherent beliefs are, the more likely they are true together." [Shogenji (1999), p. 338] However, Shogenji does not agree with our formal interpretation of this intuitive notion of 'hanging together', since he concludes that "[t]he more coherent two beliefs are, the stronger is the positive impact of the truth of one on the truth of the other." [Shogenji (1999), p. 338]

observational data depends on the informativeness of the theory. Theorem 3.2 shows that if we fix the amount of information provided by the theories relative to the observational data, then that theory coheres more with the observational data which is more probable in the light of the observational data.

Both results fit our intuitions perfectly. If we would have to decide between equally probable theories given the data, we would choose the more informative one. We would choose the more informative one, because we would get more information by the same risk of accepting a false theory. And if we would have to choose between equally informative theories, we would choose the more probable one because this one is more likely to be true. The following theorem shows a more general result concerning the relation between the presented information measures *i* and the conditional probability and the degree of coherence of a theory and the observational data.

Theorem 3.3

$$\forall p\ \forall \varepsilon>0\ \exists \delta_\varepsilon>0: p(T_1|E)>0\ \&\ p(T_1|E)\geq p(T_2|E)-\varepsilon\ \&\ i_p(T_1,E)\geq i_p(T_2,E)+\delta_\varepsilon \Rightarrow C_{O,p}(T_1,E)>C_{O,p}(T_2,E)$$

This theorem shows that Olsson's coherence measure weighs between the two epistemic virtues of a theory, i.e. its probability and its informativeness. A theory T_1 can cohere more with the evidence than another theory T_2 even if the conditional probability of the latter is higher than the conditional probability of the former. This happens if the amount of information about the observational data E provided by T_1 is sufficiently higher than the amount of information provided by T_2. This shows that a more informative theory can display a higher degree of coherence with the observational data than a less informative theory. It suffices that the difference between the conditional probabilities of both theories is small enough relative to the difference in their informational value. It should be recognized that this theorem states a further condition Huber (2008) imposes on plausibility-informativeness assessment functions, namely that "any surplus in informativeness succeeds, if the shortfall in plausibility is small enough" [Huber (2008), p. 6]. Huber dubs this requirement *continuity*.

We can conclude that the degree of coherence between a theory and the observational data depends on both epistemic virtues of theories, at least with respect to the

Olsson (2002) measure of coherence: the probability of the theory in the light of the evidence and its informativeness.

3.2 Probability, Informativeness and Shogenji's Measure of Coherence

For the Shogenji (1999) measure of coherence we can prove very similar theorems as for the Olsson (2002) measure of coherence. Now let us take a look at the Shogenji (1999) coherence measure.

Definition 3.2

$$C_{S,p}(A_1,\ldots,A_n) = \frac{p(A_1 \wedge \ldots \wedge A_n)}{p(A_1) \times \ldots \times p(A_n)}$$

if $p(A_i) > 0$ for all i: $1 \leq i \leq n$, and 0 otherwise.

Shogenji (1999), unlike Olsson (2002), also defines the term 'the sentences A_1, ..., A_n are coherent'. It is defined as follows.

Definition 3.3

The sentences A_1, ..., A_n are coherent iff $C_{S,p}(A_1,\ldots,A_n)>1$

The underlying intuition of both definitions is that the coherence of sentences depends on how much the sentences mutually support each other. They are coherent if there is at least some positive probabilistic dependency between them. And they are more coherent than other sentences if the positive probabilistic dependencies between them surpass the positive probabilistic dependencies of the others.

As already said, for the Shogenji (1999) measure of coherence we can prove similar theorems as for the Olsson (2002) measure. From the above definition of the coherence measure it is easy to obtain that:

Theorem 3.4

If $p(T_1|E) = p(T_2|E) > 0$, then:

$C_{S,p}(T_1,E) > C_{S,p}(T_2,E)$ ™ $cont_p(T_1) > cont_p(T_2)$

We can also prove the following result:

Theorem 3.5

If $cont_p(T_1) = cont_p(T_2) > 0$, then:

$C_{S,p}(T_1,E) > C_{S,p}(T_2,E)$ ™ $p(T_1|E) > p(T_2|E)$

The comments on these theorems are the same as for the theorems 3.1 and 3.2. A remarkable difference between the Olsson (2002) and the Shogenji (1999) measure of coherence is that the degree of coherence according to Olsson's measure depends on the informativeness of a theory as specified in the information measure *i*, whereas the degree of coherence according to the Shogenji (1999) coherence measure depends on the content of a theory as specified by the measure *cont*.

Again we can prove a more general result, which indicates that the Shogenji (1999) coherence measure weighs between the probability and the content of a theory.

Theorem 3.6

$$\forall p\ \forall \varepsilon>0\ \exists \delta_\varepsilon>0\text{: } p(T_1|E)>0\ \&\ p(T_1|E)\geq p(T_2|E)-\varepsilon\ \&\ cont_p(T_1)\geq cont_p(T_2)+\delta_\varepsilon \Rightarrow C_{S,p}(T_1,E)>C_{S,p}(T_2,E)$$

We can conclude that also according to the Shogenji (1999) measure of coherence the degree of coherence between a theory and the observational data depends on the probability of the theory and its content. This proofs that there is a dependency between the degree of coherence of a theory and the observational data and the probability of the theory given the observational data, and the content of the theory. Additionally the above result shows that the Shogenji (1999) coherence measure fulfills Huber's *continuity* requirement, too. The remarkable difference is that whereas for Olsson's measure of coherence *continuity* holds true with respect to the informativeness of the theory (in the sense of *i* the Shogenji (1999) measure of coherence satisfies *continuity* with respect to the content measure *cont*.

4. The Coherence Measures are Good Theory Assessment Functions

In this section we will present a theorem, which shows that the coherence measures of Olsson and Shogenji are indeed good assessment functions. Therefore we have to show that the coherence measures of Olsson and Shogenji fulfill the requirements on good assessment functions we laid down in the first section. We required that they favor true theories over false theories and that they favor true theories with more content over true theories with less content, since the former are more informative than the latter. In the last section we already got a hint that both coherence measures have this property. The theorems 3.3 and 3.6 showed that a more informative theory or a theory with greater content can cohere more with the observational data if the difference in their conditional probability is small enough. Now the basic idea[4] for the proof that the coherence measures are good assessment functions is the following: by the Gaifman-Snir Theorem (Gaifman/Snir 1982) we know that the conditional probability of a true theory tends to its truth-value if confronted with a separating sequence of sentences. Suppose we confront two true theories with such a sequence of observational data. Then the conditional probabilities of both theories tend to 1 since those theories are true. As a consequence the difference of their conditional probabilities becomes smaller and smaller. This opens up the opportunity that the theory with the greater content coheres more with the separating observational data, than the theory with less content.

The theorem, which shows that the coherence measures of Olsson and Shogenji are indeed good assessment functions, is the following:

Theorem 4.1

Let $e_0, \ldots, e_n, \ldots$ be a sequence of sentences of a first-order-language $\boldsymbol{L}$ which separates $\mathbf{Mod}_L$, and let $e_i^w = e_i$, if $w|=e_i$ and $\neg e_i$ otherwise. Let p be a strict (or regular) probability function on $\boldsymbol{L}$. Let p^* be the unique probability function on the smallest σ-field $\boldsymbol{A}$ containing the field $\{Mod(A): A \in \boldsymbol{L}\}$ satisfying $p^*(Mod(A))=p(A)$ for all $A \in \boldsymbol{L}$, where $Mod(A)=\{w \in \mathbf{Mod}_L: w|= A\}$ and $\mathbf{Mod}_L$ is the set of all maximally-consistent sets of sentences of $\boldsymbol{L}$ including instances.

Then there is an $X \subseteq \mathbf{Mod}_L$ with $p^*(X)=1$ such that the following holds for every $w \in X$ and all theories T_1 and T_2 of $\boldsymbol{L}$.

If $C=C_{O,p}$ or $C=C_{S,p}$ then

1. if $w|=T_1$ and $w|= \neg T_2$ then

   $\exists n \ \forall m \geq n: [C(T_1, E_m^w) > C(T_2, E_m^w)]$

2. if $w|= T_1 \wedge T_2$ and $cont_p(T_1) > cont_p(T_2)$ then:

   $\exists n \ \forall m \geq n: [C(T_1, E_m^w) > C(T_2, E_m^w)]$

where $E_m^w = e_1^w \wedge \ldots \wedge e_m^w$.

[4] This very idea for the proof of the following theorem is borrowed from Huber (2008), too.

This theorem shows that if we compare two theories, one of them true and one of them false, then the true theory coheres more with the observational data than the false theory (after finitely many steps of observation and for every observation thereafter). And it also shows that if we compare two theories, both of them true, but one of them with more content than the other, then the theory with more content, i.e. the more informative theory, coheres more with the observational data than the theory with less content (after finitely many steps of observation and for every observation thereafter). In this sense both measures of coherence are truth-conducive and even more than this, since they lead us to theories that are *informative* and *true*.

Both of these claims hold true if two conditions are satisfied. First, the observational data must be of such a kind that they separate the set $X \subseteq \mathbf{Mod}_L$ with $p^*(X) = 1$. Second, it does hold true in every world w of some subset $X \subseteq \mathbf{Mod}_L$ with $p^*(X)=1$. That the latter condition must be satisfied is a problem of Bayesian updating of probability functions in general. See for example chapter 6 of Earman (1992) for further discussion of this problem. The condition that the observational data must separate the set $X \subseteq \mathbf{Mod}_L$ is problematic, too. It is problematic, since a sequence must include all atomic formulae of the language $\boldsymbol{L}$ or their negations to separate $\mathbf{Mod}_L$ (and by this separate all subsets X for which it can hold that $p^*(X)=1$). This means that theorem 4.1 does not speak about theories that are formulated in theoretical vocabulary, i.e. vocabulary which includes non-observational terms; but such theories are common in everyday scientific practice.

However, there are some philosophers who should not think this is problematic, since they claim that an anti-realistic position with respect to scientific theories is preferable. According to van Fraassen (1980: 9) scientific realism is ”the position that scientific theory construction aims to give us a literally true story of what the world is like, and that acceptance of a scientific theory involves the belief that it is true.” Advocates of an anti-realistic point of view deny this. Van Fraassen (1980) mentions two alternative sorts of anti-realistic positions. The first sort of an anti-realistic position is that scientific theories are not literally true or false, but are true or false if properly construed. According to this first position theoretical terms within scientific theories do not refer like any other terms. Therefore sentences containing them are not literally true or false. However, a sentence, if properly construed, can be true or false and must therefore be a sentence which does not include any theoretical terms. The second sort of an anti-realistic position is that scientific theories are literally true or false, but the acceptance of a theory does not involve the belief that it is true. Instead we accept theories, they say, because the theory posses other virtues like empirical adequacy. Anti-realists of both sorts should not have problems with the condition that the observations must separate $\mathbf{Mod}_L$. Anti-realists of the first sort claim that theories that are literally true or false do not contain theoretical vocabulary. Since they also claim that scientific theories, if properly construed, are true or false it must mean scientific theories, if properly construed, do not contain theoretical terms. So an anti-realist of the first sort does not have any problems with that condition. An anti-realist of the second sort will not have any problems with the condition that the observations must separate $\mathbf{Mod}_L$ either. According to her position accepting a theory does not involve the belief that it is true but only that it is empirically adequate.

Suppose a theory T contains theoretical terms, and suppose theory T' is the logically strongest theory which is implied by T and which does not contain any theoretical terms. Then intuitively the following holds: T is empirically adequate iff T' is true. Theorem 4.1 shows that if T_1 is empirically adequate and T_2 is not, then T_1' coheres more with the observational data than T_2' after finitely many steps of observations. If we additionally want to introduce the comparative concept 'is more empirically adequate than' the following requirement seems reasonable: If T_1 and T_2 are both empirically adequate then T_1 is more empirically adequate than T_2 iff $cont(T_1')>cont(T_2')$. $cont(T_1')$ and $cont(T_2')$ can be said to measure the amount of *empirical* content of T_1 and T_2 respectively, not their overall content. By theorem 4.1 we also know that if T_1 and T_2 are both empirically adequate, then T_1' coheres more with the observational data than T_2' after finitely many steps of observations iff T_1 is more empirically adequate than T_2. By evaluating theories which do not contain theoretical terms we can therefore determine which theories, containing theoretical terms, are empirically adequate, and which are more empirically adequate than others. This shows that an anti-realist of the second sort can use the coherence measures of Olsson (2002) and Shogenji (1999) to assess theories, without worrying about the precondition that the observational data must separate the set $\mathbf{Mod}_L$. We conclude: at least for anti-realistic positions with respect to scientific theories the problem of theory assessment seems to be sufficiently solved by the coherence measures[5].

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[5] This point is already noted in Huber (2005) footnote 1. I also owe thanks to Franz Huber for helping me to make this point more precise.

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