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# Bayesianism as a Set of Meta-criteria and Its Social Application

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This paper aims at giving a general outlook of Bayesianism as a set of meta-criteria for scientific methodology. In particular, it discusses Social Bayesianism, that is, the application of Bayesian meta-criteria to scientific institutions. From a Bayesian point of view, methodologies and institutions that simulate Bayesian belief updating are good ones, and those with more discriminatory power (measurable by likelihood ratio) are better ones than those with less discriminatory power, other things being equal. This paper applies these ideas to a particular issue: diversity in science. Bayesian considerations reveal some conditions for epistemically desirable diversity in science.

【Key Words】 Bayesianism, Two-level theory, Social epistemology, Diversity, Mutual checking

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Bayesian Epistemology has been largely an individualist epistemology, in which degrees of belief play a central role and beliefs are, almost by definition, held by individual scientists. This paper aims at socializing Bayesianism. The word 'social' can mean various different things, but it is used here to refer to scientists as a collective, i.e. a scientific community together with its rules, institutions and so on. Thus, socializing Bayesianism means using Bayesian thinking at the collective level. Such an extension opens up new possibilities of Bayesian epistemology, and the aim of this paper is to show the fruitfulness of such attempt by outlining what a socialization of Bayesianism might be.

This is a part of a larger project of reinterpreting Bayesianism as a meta-level epistemology, rather than a methodology directly used by scientists[1]. Even though Bayesian statistics is gaining wide popularity in various corners of science, by no means it is a methodology for everyone. The contexts it can be applied is still limited, and vast majority of methodology used by scientists are apparently non-Bayesian. However, if we introduce a two-level thinking into scientific methodology, we can find a place for Bayesianism even in such cases.

The paper proceeds as follows. After seeing what Bayesian meta-criteria might look like in section 1, we proceed to a social application of such meta-criteria in section 2. For this task, we need to clarify how we can translate individualist language of ordinary Bayesianism to a collective level. This paper also looks at an concrete application, in section 3. The question I deal with in section 3 is: how

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1) The word 'methodology' is used in this paper in a very wide sense. The entire process used by scientists to get some scientific result (typically choosing among alternative hypotheses) is called methodology here. Methodologies of experimentation, observation, and simulation are methodology in this sense. Data processing methods are also methodology. Philosophical abstractions like hypothetico-deductive method and the inference to the best explanation (IBE) can also be called methodologies.

can the role of diversity in science be understood from a Bayesian point of view? The importance of diversity has been emphasized by various authors from various philosophical perspectives. However, I do not know of any work in this regard from a Bayesian perspective. Thus, I will try to show that we can gain a better understanding of the role of diversity by introducing a Soical Bayesian perspective.

One thing I do not attempt to do is to justify Bayesianism itself. This is a widely discussed issue and should be done elsewhere. The arguments in this paper will, if successful, contribute to an alleviation of some of the objections to Bayesianism based on the demandingness of Bayesian calculation. But this does not address other objections to Bayesianism, such as the objection that there is no rason (including the Dutch Book argument) why our degrees of belief should obey the rules of probability calculus.

## 1 Bayesianism as a set of meta-criteria

### 1-1 What is Bayesianism

First, let me outline the theoretical background. Bayesianism in the philosophy of science is a position in confirmation theory that emphasizes probabilistic thinking in the assessment of the plausibility of a scientific hypothesis. According to Bayesianism, our degree of belief in hypotheses should obey the axioms of probability calculus, and this implies that the degree of belief of a certain hypothesis given certain evidence should obey the so-called Bayes theorem:

$$P(h, e) = P(e, h)\ P(h) / P(e)$$

Here, P(h, e), the probability of hypothesis h given evidence e, is called *posterior probability*, and it is a function of P(e, h) (e's probability given h, called *likelihood of h*), P(h) (h's probability, called *prior probability*), and P(e) (e's probability, called *expectedness*). Bayesianism analyzes the inference process of scientists (both normatively and descriptively) using this scheme.

### 1-2. The two-level theory and Bayesianism

Bayesianism has its virtues and shortcomings. A glaring shortcoming is that actual scientists rarely think in Bayesian terms; moreover, it would be undesirable for a scientist to try to use Bayesianism consciously because it would take up too many computational resources and require information we do not have in order to calculate posterior probabilities for each piece of evidence. It is therefore natural that many philosophers of science have criticized Bayesianism as being unrealistic.

On the other hand, when understood as a background rationale behind various methodological rules and wisdoms, Bayesianism has a strong unificatory power. For example, it can reconstruct the hypothetico-implication method as an extreme case of the Bayesian inference, where deduction h -> e is replaced with P(e, h)=1. It can also give explanation to such various methodological rationales that repeating the same experiment over and over is not desirable or that ad hoc hypotheses are not desirable.[2)]

Given these characteristics, Bayesianism can be best understood as a meta-criterion (or a set of meta-criteria) that is not (and probably should not be) used as a consciously obeyed rule by individual scientists, but used to evaluate such conscious rules at a meta-level (Iseda 2001).

This view is inspired by R.M. Hare's two-level theory of

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2) Howson and Urbach (2006), ch. 4.

utilitarianism. In utilitarian ethics, the two levels are critical level and intuitive level (Hare 1981). Intuitive rules are chosen at the critical level so that obeying these rules in our daily life tends to maximize utility. When intuitive rules conflict with each other (i.e. moral dilemma), or when there is no appropriate rule for a new situation, we go back to the critical level and apply the principle of utility directly to individual case. However, in all other cases, we are supposed to stick to intuitive rules (so these rules are not mere rules of thumb). Utilitarian calculation involves many variables that cannot be determined in a purely objective manner (though, of course, not purely subjective either). When we have a room for choice, interpreting the situation to our advantage (such as underestimating bad consequences of an action when the person wants to do it) is very tempting. Thus such calculation has a lot of rooms for biases to sneak in. An action based on such biased calculation will not maximize utility; in other words, utilitarianism itself warn us against conducting utilitarian calculation. Actors need to take intuitive rules very seriously. This is what deontologists would say, so by saying this, Hare's two level theory tries to reconcile the debate between utilitarianism and deontology.

Similar considertations are applicable to Bayesian epistemology. The probabilities to be plugged in Bayesian calculation are not determined objectively. Some people would say the value is totally arbitrary, but most people would agree that there are reasonable probability assignments and unreasonable ones. It is likely that when we are calculating in accordance with Bayes's theorem, we unconsciously bias our probability assignments to the advantage of our pet theory, which makes the result unreasonable even from a Bayesian point of view. To guard against such possibility, it is desirable that we do not apply Bayesian calculation directly to individual cases. Rather, Bayesianism should be used as a meta-criterion (or a set of meta-criteria) for choosing intuitive rules of theory choice.[3)]

### 1-3 Bayesian meta-criteria

What exactly are the criteria? Bayesianism as a decision rule is basically an empiricist epistemology that requires us to accept a hypothesis that has the highest posterior probability given the total evidence. This criterion can be applied indirectly in the form of choosing conscious rules that satisfies the requirement. We can formulate this idea as follows (which I call Bayesian Meta-Criterion 1, BMC1 henceforth):

> BMC1: A methodology used by scientists is desirable if and only if it tends to tell us to accept the hypothesis with highest posterior probability, or reject hypotheses with lower posterior probability, under the ordinary conditions it is adopted.

The clause on the ordinary conditions is added because simple rules have their scopes. A comparison with the two-level theory based on utilitarianism helps here. Simple rules like ‘do not lie’ and ‘do not kill’ tend to increase utility, but we can easily construct unusual thought experiments in which obeying simple rules have a disastrous result in terms of utility (such as the case in which telling the truth to a terrorist jeopardizes people's lives). However, such unusual thought experiments

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3) One of the referees pointed out that criticisms against consequentialism may become applicable to the present view because of this analogy. I agree that Bayesianism as a set of meta-criteria faces the similar criticisms as utilitarianism, but most of the criticisms are already directed to Bayesianism; that is, analogy between Bayesianism and utilitarianism does not create new criticisms because the criticisms that can be produced that way already exist (such as the unrealistic nature of the calculation and counter-intuitive conclusions). As I explained at the beginning, this paper does not address the issue of justification of Bayesianism itself.

do not mean that the simple rules are useless; rather, they mean that they are useful only under the ordinary conditions. Similarly, for any simple methodological rules scientists adopt, we can construct a story about unusual cases in which the methodology leads to a disastrous choice from a Bayesian point of view. This simply means that the method should be used within the appropriate scope, rather than it is wrong.

One application of BMC1 is a Bayesian justification of significance test. Bayesianism and significance tests used in classical statistics are supposed to be conflicting positions in philosophy of statistics, but they are reconciliable if we introduce two levels in scientific methodology. Bayesians can also admit that siginificance tests have a good consequence under the ordinary circumstance. Suppose that a result e that rejects a null hypothesis h under the given significance level is obtained. This means that likelihood of h, P(e, h), is small. Let us add the condition that there are alternative hypotheses $h_i$ as plausible as h, and that some of those alternative hypothses have higher likelihood with e, that is $P(e, h) \ll P(e, h_i)$ for some $h_i$. If this condition is met, h cannot be the hypothesis that have the highest posterior probability, and it is a good thing even for Bayesians to reject (i.e. decide not to believe) h. Typical Bayesian objections to significance tests[4] use situations in which this condition is not met, but such situations are simply not within the scope of this methodology.

One peculiar feature of BMC1 is that the set of belief accepted through a methodology justified by BMC1 may well be contradictory as a set.[5] This is a problem known with the name of the lottery paradox, and it is endemic to any scheme that convert high degree of belief into

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4) Such as Howson and Urbach (2006), pp. 154-6.

5) I am thankful to the refree who pointed out to me that I have to make clear my position on this regard.

an acceptance of a claim (and low degree of belief into rejection) in a binary sense.[6] A full treatment of the lottery paradox will call for another paper, but let me give an outline of my position.

The analogy with utilitarian ethics again helps to elucidate the position. In the case of utilitarian theory, intuitive rules of conduct are rough approximation of utilitarian calculation, and they often conflict with each other (so called moral dilemma). When we have such a conflict, according to the two-level theory, we go back to the critical level of utilitarian calculation and settle the issue. Similarly, from a Bayesian point of view, binary acceptances/rejections of a claim accoding to a given scientific methodology can be seen as useful but somewhat inaccurate summary report of our degree of belief (let us use abbreviation SISR for 'somewhat inaccurate summary report'). As SISRs, we should not assume that a logical opperations on accepted beliefs always lead to valid conclusions, even though such operations usually lead to torelably good conclusions. On the other hand, thinking always in terms of probabilistic acceptance will make our life intorelably hard. Thus, the two-level theory of Bayesianism recommends that we use simple methodology with binary conclusions for most purposes. However, in exceptional cases, we should remember that what scientists conscously do is a rough approximation of the Bayesian calculation using SISRs, and if necessary, we should go back to the Bayesian level of thinking.

BMC1 is not the only possible meta-criterion from Bayesianism. If all that proponents of Bayesianism want is consistency with the evidence,

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6) The most common case of the paradox is a lottery with n tickets with which exactly one of the tickets wins. Here, the beliefs "ticket 1 is not a winning ticket", "ticket 2 is not a winning ticket"… "ticket n is not a winning ticket" have high probability, and the belief "one of the n tickets is a winning ticket" has a probability of unity, but put together these beliefs are contradictory.

they would not care what kind of evidence they have; but as a matter of fact, they do care about the quality of evidence. Bayesians prefer having “good” evidence defined in terms of Bayes factor, P(e, ~h)/P(e, h); the larger the Bayes factor is, the better the evidence e[7]. More generally, so-called likelihood ratio, P(e, h1)/P(e, h2), surves as a measure of goodness of evidence between two hypotheses h1 and h2[8]. These observations suggest that Bayesianism supports another meta-criterion(which I call BMC2 henceforth):[9]

> BMC2: All other things being equal, a methodology more efficient in terms of discriminating hypotheses, i.e. giving widely divergent posterior probabilities to hypotheses, is more desirable than a less efficient methodology.

To see how BMC2 works, think of crutial experiments. Suppose there are two mutually exclusive and collectively exhaustive hypotheses h1 and h2 (where P(h1)=P(h2)=0.5), and we have to choose one of two experiments e1 and e2 to test the hypotheses. Suppose that both of the experiments have two mutually exclusive and collectively exhaustive outcomes, o11 and o12 for e1, and o21 and o22 for e2. Suppose further that the experimental results have the following likelihoods:

e1: P(o11, h1) = 0.9, P(o11, h2)=0.3, P(o12, h1)=0.1, P(o12, h2)= 0.7
e2: P(o21, h1) = 0.6, P(o21, h2)=0.4, P(o22, h1)=0.4, P(o22, h2)= 0.6

Whichever experiment is chosen, and whatever result is obtained, the

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7) Howson and Urbach (2006), p. 97.

8) Ibid., p. 155.

9) A keen reader might have noticed that BMC1 is formulated in absolute terms, while BMC2 is formulated in comparative terms. As a matter of fact, we can think of a comparative version of BMC1 and absolute version of BMC2. I omitted those alternatives to keep the story as simple as possible.

posterior probability of h1 and h2 changes, which means the one of two hypotheses are preferred by the experimental result. Thus, from the point of view of BMC1, both experiments (together with appropriate decision rule) are acceptable. However, the discriminatory powers of the two experiments are different. Applying simple Bayesian calculation, we obtain the following posterior probabilities:

e1: P(h1, o11) = 0.75, P(h2, o11)=0.25, P(h1, o12)=0.13, P(h2, o12)= 0.88

e2: P(h1, o21) = 0.6, P(h2, o21)=0.4, P(h1, o22)=0.4, P(h2, o22)= 0.6

We can see that e1 tend to give more extreme values than e2, which means that we are more confident in the hypothesis we choose after conducting e1 than we are after e2. BMC2 tells us to use e1 rather than e2, if we have to choose.

We can make the idea a bit more mathematically precise. The most ordinary measure of the discriminatory power is the likelihood ratios; the further the ratio is from one, the stronger the discriminatory power of the evidence. As an extention of this idea, we can say that an experiment that tends to have results with larger discriminatory power (i.e. more extreme likelihood ratios) is stronger than one with smaller discriminatory power.[10)]

It seems to me that BMC2, rather than BMC1, is the criterion used in evaluating most methodological rules of scientific inquiry. Even in the

10) Taking the average of likelihood ratios is an obvious way of obtaining this measure. However, before averaging, likelihood ratios should be adjusted so that smaller likelihood is always used as the denominator (otherwise, averaging cancel out extreme likelihood ratios in the opposite direction). To apply this idea to the current case, e1 has adjusted likelihood ratios P(o11, h1) /P(o11, h2) =3, P(o12, h2)/P(o12, h1)=7, with the average ratio of 5.5, while e2 has ratios 1.5 and 1.5, with the average ratio is 1.5.

case of significance test, which can be justified from BMC1's point of view, a more appropriate justification comes from BMC2. In a situation in which we conduct a significance test, there are many different things we can do: merely guessing, conducting a qualitative research, other types of quantitative research, etc. BMC1 accept less efficient methods as long as their evaluation of hypotheses is in accord with the posterior probability. In an extreme case, even if the research method has little influence on posterior probabilities, i.e. tend to yield evidence such that P(h, e)=P(h), BMC1 accepts the method as long as it tells us to choose a hypothesis that has the highest prior probability. However, we have a good reason to choose a siginificance test rather than such inefficient tests. A significance test is more efficient than most other available methods (including the extreme one just mentioned) in detecting a false null hypothesis, and Bayesians (not classical statisticians) can represent the detection as a sudden drop in posterior probability of the null. This thought is captured by BMC2.

This example can also be used to explain why the ceteris paribus clause “all other things being equal” exists in BMC2. After all, a significance test is not a perfect method, especially from a Bayesian point of view. An application of Bayesian statistics provides us with posterior probabilities directly, and we can devise a more efficient test using Bayesian statistics. However, Bayesian statistics tends to call for more computational resources, and tends to be less clear-cut in terms of final decision (such as rejecting the null). So, if the research situation is such that the researcher has a limited computational resources and needs clear-cut decision, BMC2 allows us to prefer a significance test over a Bayesian statistical method. In other words, all other things are not equal between Bayesian statistics and a significance test.

Of course, BMC1 and BMC2 are a first approximation that calls for further examination and refinement. However, they suffice for the purposes of the present paper.

## 2 Social application of Bayesianism

Let us move on to the extension of Bayesianism to social contexts. This may sound puzzling. A natural interpretation of Bayesianism is individualistic; degrees of belief are psychological properties attributable to an individual. Thus, it is natural to interpret that Bayesianism deals only with individual psychological processes.

However, this does not mean that Bayesianism cannot be extended to social context. ‘Social epistemology’ is the term to refer to philosophical analyses of societal aspects of science, so what I am proposing here is to apply Bayesianism to social epistemology. There are at least three different types of such application. The first is an analysis of behavior of Bayesian agents as a collective. The second is an extension of the notion of degree of belief to a societal level. The third is the application of Bayesianism as a meta criterion to societal matters. Let us call the third type of application Social Bayesianism.

### 2-1 Outline of three types of socialization

(1) Investigation of the behavior of a community of Bayesian agents

The first approach is an epistemological analysis of a community of Bayesian agents. In this case, Bayesianism is used as an idealized description of the agents' inference processes. A representative work in this regard is the study by Alvin Goldman and Moshe Shaked, in which they showed that a community of credit-seeking Bayesian agents does better than that of truth-seeking Baysian agents in the efficiency of attaining true beliefs at least under certain conditions.[11] Goldman also develops a veritistic account of Bayesian inference on testimony.[12)]

This is a kind of application of Bayesianism, indeed, but this is not a kind of Bayesianism as a normative theory. The overall framework of evaluation in the study by Goldman and Shaked is veritism, rather than Bayesianism; Bayesianism is used for model building here.

(2) Investigation of the ways of constructing societal degrees of belief from individual degrees of belief

The second approach deals with the extension of the notion of the degree of belief to a community. If we want to assess a scientific community as an epistemic subject, from a Bayesian point of view we need to find a way to attribute a degree of belief to a community. We do not have to assume that a community has a "collective mind," or something like that, for such an attribution (though, of course, the metaphysical issue of collective mind is an interesting topic). All we need is a measure of a collective degree of belief that meets several desiderata (the measure needs to obey the laws of probability calculus; the measure should have some relationship with individual degrees of belief in the community; the measure should have intuitive appeal; and so on).

A recent study by Shaffer (2008) presumes that for an epistemic community to have a shared belief, all the members of the community should have one and the same belief. However, other authors have a more relaxed notion of shared degree of belief. A classical work in this regard is the one by Keith Lehrer and Carl Wagner (Lehrer and Wagner 1981). They proposed to take a weighted average of individual degrees of belief. Pointing out certain shortcomings of their approach, Isaac Levi proposed an alternative that allows a kind of indeterminacy in degrees

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11) Goldman (1992), ch. 12.

12) Goldman (1999), ch. 4.

of belief, which he originally developed for individual degrees of belief and later extended to collective ones (Levi 1974, 1990). There is a more recent attempt by Dietrich and List (2010) in a similar direction.

Even though these studies deal with Bayesianism at a collective level, it may not be appropriate to call the approach "social." Sociologists often regard interaction among people as the crucial feature of society. On the other hand, the common feature of the proposals by Lehrer and Wagner on the one hand and Levi on the other is that they look at an epistemic community as a static entity, disregarding the dynamic process of consensus formation; in short, there is no need for interaction in their schemes. Of course, this does not mean that we cannot have a theory of collective degrees of belief based on a dynamic process. This is an interesting and challenging enterprise, but should be left for another occasion.[13)]

Another point to note is that Bayesianism is not used normatively in this approach. Construction of collective degrees of belief is an interpretive enterprise that proposes an understanding of epistemic community. Of course, once a measure of collective degrees of belief is constructed, it can be used for normative purposes, but the construction itself is a different issue.

(3) Investigation of desirability of various social institutions using Bayesianism as a meta-criterion, or Social Bayesianism

If we stick to the view that Bayesian epistemology is used directly by scientists, socialization of Bayesianism should take one of above two

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13) Iseda (2006) made a preliminary attempt at revising Levi's idea about societal belief by introducing the notion of expert. The paper does not raise the issue of dynamic aspect of collective belief explicitly, but some types of expertism can be seen as dynamic processes where the degree of belief of a community is determined based on that of experts.

forms; either we deal with a group of scientists who use Bayesianism directly, or we regard a collectivity as an agent who directly utilizes Bayesian epistemology. Seeing Bayesianism as meta criterion (or a set of meta criteria) opens up another possiblity. This third approach is a streightforward extention of Bayesianism as a normative theory. To signal the streightforwardness, let us use the expression Social Bayesianism for this particular type of application in this paper (even though the eariler two types can also be called Social Bayesianism in other senses).

Just as individual methodological rules can be evaluated from a Bayesian point of view, social institutions can be the object of assessment. For example, if one system of peer review is better than others in terms of helping us update our degrees of belief, the system will be positively evaluated. If we have a measure of collective belief (constructed in the second approach), the evaluation can also be made in terms of collective degrees of belief.

In Social Bayesianism, the role of Bayesian evaluation is similar to that of veritism in Goldman and Shaked's work. In veritism, an institution is evaluated in terms of its features related to the production of true beliefs (reliability, efficiency, power, etc.). On the other hand, according to Social Bayesianism, what is important is having a good institution in Bayesian terms.[14)]

Are there existing studies in this category? Even though there are several empiricist approaches in social epistemology (such as Longino 1990 and Solomon 2001), they do not put forth any particular theory of the evidence-hypothesis relationship. Avowed Bayesians who are interested in social epistemology, such as Alvin Goldman, do not use

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14) This does not mean that veritism and Bayesianism are incompatible. Indeed, veritism and Bayesianism can be made compatible by assuming that our probability assessments are “realistic” (i.e. correspond to reality).

Bayesianism as an evaluative scheme, preferring the first two approaches above. Thus, even though the third approach is a natural extension of Bayesianism as a set of meta-criteria, it has largely been ignored as a possibility so far.[15)]

### 2-2 Outline of Social Bayesianism

Now we know the basic idea of Social Bayesianism. How can we spell out the details of the idea? Let us look at further several aspects of the idea.

What are the candidate of the items to be evaluated from Social Bayesianism? In the field of social epistemology, wide range of social institutions has been discussed. Trust in experts and witness (Goldman 1992), rules of credit ascription (Goldman 1992), cognitive division of labor (Kitcher 1990), authoritarianism (Kitcher 1993), rules for settling scientific debate in public arena (Longino 1990), disagreements among scientists (Hull 1988), various systems of peer review (Kihara 2003), and so on. Some of those items are too informal to be called ‘institutions’ in an ordinary sense, but as a matter of convinience, let us use the term ‘scientific institutions’ to refer to these items generally.

How does Social Bayesianism evaluate those scientific institutions? As we noted above, there are at least two Bayesian meta-criteria, BMC1 and BMC2 applicable to scientific methodology. There is no reason to assume that they cannot be applied to scientific institutions in general. To make the application explicit, let us reformulate BMC1 and BMC2 as applied to scientific institutions (Social Bayesian Meta-Criteria 1 and 2, SBMC1 and SBMC2 for short).

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15) A possible exception is Iseda's work (2001, pp. 134-8), which includes an attempt to account for the so-called “special reasons requirement” from a Bayesian point of view, and if we interpret social institutions in a broad sense, this can count as an example of the third approach.

SBMC1: A scientific institution is desirable if and only if it tends to lead scientists to accept the hypothesis with highest posterior probability, or reject hypotheses with lower posterior probability, under the ordinary conditions it is established.

SBMC2: All other things being equal, a scientific institution more efficient in terms of discriminating hypotheses, i.e. giving widely divergent posterior probabilities to hypotheses, is more desirable than a less efficient institution.

How can these two criteria be applied to scientific institutions? Even though we are going to have a detailed case study with the role of diversity in science, it is desirable to see how these criteria work with an illustration at this point.

Take the ordinary peer review system as an example. Peer review is a system in which the scientific value of a paper is evaluated ('refreed') by other scientists (desirably in the same field) prior to the publication in an academic journal. The procedure often involves revisions of the refreed paper based on reviewer comments. Various 'blind refree' systems are often adopted to ensure the objectivity of the refree judgments. Reviewers conduct multiple tasks during the review, and one of their important tasks is checking if appropriate methodology required in the field is applied in the paper.

When we think in terms of degree of belief, the notion of 'peer review system' should be taken widely, including the effects of the procedure to the degrees of beliefs of various people. In general, everybody, including the authors, reviewers, editors, publishers, other scientists in the same field and other people (who may or may not be scientists) have higher confidence in the contents of the paper after they learn that the paper passed a peer review, and the rigidity of the refree system of a journal contribute to the confidence in the papers published in the journal. On the other hand, everybody also knows that sometimes bogus papers escape the keen scrutiny by reviewers and get published in top journals, while good revolutionary papers are sometimes rejected.

To apply SBMC1, let h and e be the following:

h:the paper is reliable
e:the paper passed a peer review system

Here, P(e, h) may not be high for top journals, but P(e, ~h) is supposed to be very low compared with P(e, h). As a result, The posterior probability P(h, e) tends to be very high, and for most cases higher than P(~h, e).[16] Believing h rather than ~h after peer review is thus justified in Bayesian terms. In other words, the system meets the requirement of SBMC1.

To apply SBMC2, we have to compare the peer review system with other similar systems. There are many different publication systems; publication without any review, review by an editor who is not specialized in the field, and so on. Let us compare e with the following alternatives:

e1: the paper is published without review
e2: the paper is published after an editorial review by a non-specialist

Is likelihood ratio P(e, h)/P(e, ~h) more extreme than P(e1, h)/P(e1, ~h) or P(e2, h)/P(e2, ~h)? If yes, the peer review system is justified under SBMC2 against those alternative methods.

Is there any argument against the claim that P(e, h)/P(e, ~h) has a extreme value? It is often pointed out that scientists in the same field

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16) In some cases, the prior probability of h is so low that even passing peer reviewing is not enough for h to be accepted. This applies to certain extraordinary claims, such as finding evidence for extrasensory perception.

may not be the ideal reviewer. They can easily identify the author from the content even under a blind refree system, and the reviewer may have personal contact with the author, which may bias the review. With all these possibilities, specialists in the same field are still supposed to be much better at detecting methodological flaws of a paper than a non-specialist, and this virtue seems to overwhelm the shortcomings of a biased review. Under these conditions, P(e, h)/P(e, ~h) should be much more extreme than P(e1, h)/P(e1, ~h) (which is very close to 1) and P(e2, h)/P(e2, ~h) (which does better than e1 but still stay around 1).

There may be other publication systems that are more efficient in descriminating h from ~h (adding more reviewers to counter the bias, for example). However, such systems are likely to cost (in terms of both time and money) much more than the ordinary peer review. Thus “all other things being equal” clause can rule out the comparison with such costly options. Given those considerations, the peer review system seems to be well supported by SBMC2.

The above analysis is not meant to be a serious scrutiny of the peer review system. The purpose of this analysis is an illustration of how SBMC1 and SBMC2 are supposed to work. Now let us move onto a more serious application of Social Bayesianism.

## 3 Diversity in science from a Bayesian point of view

### 3-1 Social falsificationist defense of diversity

Many of scientific institutions analyzed by social epistemology has something to do with diversity in science; scientific debates and disagreements presupposes diversity in opinion; reliance on experts is based on diversity in knowlege; divisions of labor is based on diversity in the role; and so on so forth. The purpose of this section is to apply the Social Bayesian point of view to the evaluation of the role of diversity in science. However, let us begin with looking at an existing alternative analysis.

Social epistemologists tend to evaluate diversity in various senses positively. For example, Kitcher's study of division of cognitive labor (Kitcher 1990) focuses on the role of diversity in distributing research efforts more efficiently. One of the main (supposed) virtues of diversity is its effectiveness for mutual checking. This idea is often discussed from a falsificationist point of view, which can be called ‘social falsificationism’ in the same vein as Social Bayesianism. The basic idea of social falsificationism is rather simple, and can be traced to J. S. Mill's defense of freedom of speech and what Popper calls “public character of scientific method”.[17] As a psychological fact, we are not good at criticizing ourselves. Thus, to conduct a severe test required by falsificationism, we need ‘help’ from other people, especially those who are hostile to ourselves.[18] Competing research groups function as the vehicle of such mutual checking. In recent literature, the idea has been taken up by David Hull and Helen Longino, among others (Hull 1988, Longino 1990). Since mutual checking is essential for progress and quality control, diversity seems to contribute to these concepts.

Of course, for such mutual checking to work, an epistemic community should have certain characteristics. In Longino's version, the following conditions are essential in order for a community to have knowledge.[19]

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17) Mill (1859), Popper (1950), ch. 23.

18) The role of hostility is clearly recognized in social falsificationism. Hull suggests that mutual checking may be based on not-so-nice motivations such as “to get that son of a bitch” (Hull 1988, p. 160). This is a place where seeming irrationality at the individual level can be seen as rational at the communal level.

(1) Venue: existence of the publicly recognized forums for criticism. Criticism should be valued as much as the original research.
(2) Uptake: community should be responsive to critical discourse.
(3) Public Standards: criticism should be based on shared standards
(4) Tempered Equality: there must be some kind of equality in intellectual authority, tempered with past records, training, etc.

Since these conditions are supposed to ensure the objectivity of the resulting consensus in the community, let us call these conditions the "objectivity conditions" henceforth.

### 3-2 Social Bayesian analysis of objectivity conditions

What would a Social Bayesian say to such an analsysis of diversity in science? First thing to note is that there are good Bayesian reasons for promoting falsificationist practices. Even though Bayesians disagree with the philosophical tenets of falsificationism such that mutual criticism is in itself rational or that induction is illegitimate, the practice of mutual checking can be justified in various ways, including SBMC1 and SBMC2. Just like the case of the peer review system, to be evaluated by Bayesian meta-criteria, the practice should include some belief formation and revision rules. In the case of mutual checking practice, the obvious choice is the rule that a scientific claim that survive the mutual checking process should be accepted as a credible one. Since mutual checking is an efficient tool for detecting errors, it is obvious that SMBC1 supports the mutual checking practice together with the above mentioned belief formation rule.

As to SBMC2, it can be used to justify the objectivity conditions.[20]

[19] Longino (2002), pp. 129-34.

[20] SBMC 2 can also be used to justify mutual checking itself against non-checking, but the argument is almost the same as the one used for the

If these conditions can be implemented without much cost, it is desirable to implement them from this point of view. Let us concentrate on the Venue condition and Uptake conditon.

Generally speaking, the existence of the venue for criticism tend to promote critical assessments, and lead to a more efficient detection of errors. The Uptake condition calls for the change in belief according to the detection. Suppose there are two scientific communities C1 and C2, with institutions of criticism I1 and I2 respectively. I1 and I2 are similar to each other but differ in one point, i.e. the satisfaction of the Venue condition and the Uptake condition (I1 meets the conditions while I2 does not). Both communities consider two mutually exclusive and collectively exhaustive hypotheses, h1 and h2. The arguments and supports for the two hypotheses seem to be similar, but as a matter of fact, the argument for H2 involve some unnoticed errors. Both I1 and I2 yield two mutually exclusive and collectively exhaustive verdicts for h1 and h2, namely

e11: the argument for h1 has errors.
e12: the argument for h1 has no error.
e21: the argument for h2 has errors.
e22: the argument for h2 has no error.

Suppose that P(h1)=P(h2)=0.5, after taking all the existing arguments and supports into account. Suppose further that I1 and I2 have the following likelihood assignments:

I1: P(e11, h1)= 0.1, P(e11, h2) = 0.5, P(e21, h1)=0.5, P(e21, h2)=0.1
I2: P(e11, h1)= 0.01, P(e11, h2) = 0.01, P(e21, h1)= 0.01, P(e21, h2)= 0.01

peer review system.

Under I1, if the hypothesis is wrong, there is a fifty-fifty chance that the criticism system find some error in the argument. The probability of detecting an error for a correct hypothesis is assigned the value 0.1, because, after all, it may be the case that we accept the correct answer based on an erroneous argument. For I2, since there is no error detection mechanism, we can assume that errors are rarely detected, regardless of whether the hypothesis is true or not. The average likelihood ratio is 5 for I1 and 1 for I2. these values are used to update beliefs because of the Update condition. To take an example, if e21 is obtained, P(h1, e21)=0.83 and P(h2, e21)= 0.17 under I1, and P(h1, e21)= P(h2, e21)= 0.5 under I2. Clearly SBMC2 prefers I1 in this case for its discriminatory power.

Other conditions contribute to make sure that errors are detected and accepted (i. e. to keep probabilities like P(e11, h) high). The Public Standard condition is important for the community because without it the community will have a difficulty in deciding if a criticism is fair or not. When a debate on the fairness of a criticism arises, the criticism will not be incorporated in the criticized scientific claim even if it is actually a fair one. To avoid such confusion and waste of time, having a shared standard is very important.

As to Tempered Equality, it is included to reduce the probability that a claim goes through unchecked simply because the person who made the claim has some authority. Longino, who proposed these conditions, does acknowledge the legitimacy of authority based on experience or training. However, people sometimes aquire authority because they belong to the dominant group, and the criticism to them may be ignored if the criticizer belongs to a minority group. This type of authority impedes corrections of errors, lessening the credibility of the resulting claim. Given these considerations, SBMC2 endorses the Tempered Equality condition.

### 3-3 Further conditions from a Social Bayesian point of view

If all Social Bayesian analyses do is simply authorize conditions proposed by others, we can hardly say it is a fruitful enterprise. However, Social Bayesianism, especially in its comparative forms like SBMC2, can be a strong heuristic tool. In a general form, the heuristics take the following form: if we can add a feature that makes the likelihood ratio more extreme to a given institution with little cost, the addition is probably desirable. Let us apply this to Longino's mutual checking system.

One thing we can see in the objectivity conditions is that they do not mention the productivity or effectiveness of mutual checking. This is natural for Longino because she is mainly interested in equality and objectivity in science. At this point, Social Bayesianism provides a point of view from which we can think of the productivity of various mutual checking systems.

It is obvious that the objectivity conditions do not necessarily facilitate productive and effective mutual criticisms. For example, some criticisms may be destructive in the sense that they are too fundamental to be incorporated in the criticized research. Also, objectivity conditions do not require that the members be motivated to criticize, though, of course, conditions are in place to promote criticism. Another seeming lack in the objectivity conditions is that it says nothing about the level of diversity in the community, though, again, her condition of equal authority intends to promote diversity in the community. If the community is homogeneous, giving equal authority to everybody does not ensure that the research will be critically examined from adequately diverse points of view.

We can turn these considerations into further conditions for critical properties of the epistemic community:

(5) Critical reliability: the rate of constructive criticisms in the sense of catching correctable mistakes and oversights among all criticisms should be sufficiently high.
(6) Critical power: the number of constructive criticisms made by community members is sufficiently large
(7) Critical efficiency: the community should be sufficiently efficient in the sense that the number of constructive criticisms per unit resource is sufficiently large.

Let us call these the “critical productivity conditions,” or the “productivity conditions” for short. These conditions were inspired by Alvin Goldman's veritistic conditions for a truth-conductive community .[21] The considerations given before the formulation of these conditions should be enough to show that meeting these conditions contribute to the discriminatory power of mutual checking; that is, it is rather obvious that all these conditions meet SBMC2.

Unlike the objectivity conditions, all the productivity conditions are matters of degree; how much reliability is enough depends on the context. There can be trade-offs among these conditions and/or between these conditions and other conditions (including the objectivity conditions). For example, trying to attain full-tempered equality may hinder the critical reliability or efficiency of the community. Power and efficiency also conflict with each other when putting more resources into critical activities increases power while lowering the efficiency.

This analysis reveal some of the reasons why diversity is desirable in

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[21] Goldman (1992), pp. 195-6. Goldman's list has two more items: fecundity and speed. Fecundity is about the dissemination of knowledge to the lay public, and speed is about the speed of reaching the correct answer. I omitted these because I am not sure whether these standards apply to constructive criticism.

science, and provide general advice for existing scientific institutions; if there is a chance to enhance objectivity conditions and productivity conditions without much cost, probably they should go for it. This does not mean that I maintain that mutual checking is the only epistemic reason to value diversity. There are of course other reasons why we like diversity. For example, Solomon values diversity in science because she thinks that it may be a reflection of the diverse nature of empirical evidence (Solomon 2001). Kitcher (1993) values diversity as a matter of the cognitive division of labor. I do not think that enhancing the mutual checking system compromise those other virtues of diversity.

## 4 Concluding remarks

This paper went through three levels at which Bayesian meta criteria are used. First, we saw their applications to individualistic methodology such as significance tests. Then, the idea is socialized and general idea of Social Bayesianism is explained applying SBMC1 and SBMC2 to the peer review system. Finally, we saw a more specific application of the criteria to mutual checking system proposed by Longino. I believe that I gave a clear image of what Social Bayesianism look like by going through these stages.

The criteria given in this paper (BMC1, BMC2, SBMC1 and SBMC2) and the productivity conditions for mutual checking system are pleriminary and tentative. In the case of productivity conditions, reliability, power, and efficiency are not the only aspects we care about. For example, we may want criticisms to be “good” ones, though it is hard to explicate the notion of “goodness” of criticism. However, such a preliminary study should be enough to show the fruitfulness of

Bayesianism as a set of meta criteria in general and Social Bayesianism in particular.[22)]

22) I would like to thank anonymous referees for their detecting errors in the original version of this paper.

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# 메타 기준들의 집합과 그것의 사회적 적용으로서의 베이즈주의

이세다 데츠지

이 글은 과학 방법론에 관한 메타 기준들의 집합으로서의 베이즈주의에 대한 일반적 조망을 제공한다. 특히 이 글은 사회적 베이즈주의, 즉 과학 제도들에 대한 베이즈주의적 메타 기준의 적용을 논의한다. 베이즈주의적 관점에서 보면, 베이즈주의적 신념 개정을 고무하는 방법론들과 제도들은 좋은 것이고, 다른 사정이 같다면, 가능도 비율에 의해 측정 가능한 식별력을 좀 더 많이 갖춘 방법론들과 제도들이 더 적게 갖춘 것들에 비해 낫다. 이 글은 그러한 아이디어를 특별한 주제인 과학에서의 다양성에 적용한다. 베이즈주의적 고려를 통해 과학에서의 인식론적으로 바람직한 다양성에 대한 몇 가지 조건들이 드러날 것이다.

**주요어:** 베이즈주의, 두 수준 이론, 사회인식론, 다양성, 상호 점검