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Interdisciplinary Communication and Advice under Uncertainty in a Pandemic

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ABSTRACT

Pandemic situations are volatile, uncertain, and have interdisciplinary issues. Decision support methods exist, but do not cover needs in the pandemic. We propose a Bayesian Single Pass Reasoning method (SPBR) with a calculus based on Bayes' theorem for providing evidence-based preferabilities for alternative courses of action. We demonstrate it with an example of a lockdown decision by a panel of 31 persons. We conclude that the method fulfils the needs of the pandemic and is worth to be further investigated and developed. To overcome subjectivity scientists should consider providing computed likelihoods from their causal models and simulations.

Keywords: Pandemic management, Decision making, Bayesian reasoning

INTRODUCTION

Communication and scientific advice in the COVID-19 pandemic are difficult. The situations are dynamic and volatile, and advice must be given under time pressure. Data is lacking and the pandemic, initially understood as a public health issue, soon becomes an interdisciplinary matter because measures to be taken have not only effects but also side effects: businesses are impaired; domestic violence is on the rise; the education system does not work properly; child psychiatry shows alarming growth rates; ethical and legal issues come up; societies are dividing. How can we support decision making and communication in such situations?

THE ROLE OF SCIENCE IN DECISION MAKING

Figure 1 shows four variants (a-d) of a simple role model of science-based decision making. There are three basic roles: scientist, advisor and decision maker (a). Scientific knowledge is provided by scientists. Several domains and working groups contribute to a decision (b-d). Scientists are responsible for good scientific practice in their domain. Advisors collect information from the scientific domains, develop scientifically grounded options for action and recommend possible actions. They are responsible for the quality of work in these tasks. Decision makers must decide and are held responsible for their decisions. They can be individuals or groups, such as parliaments. In case of

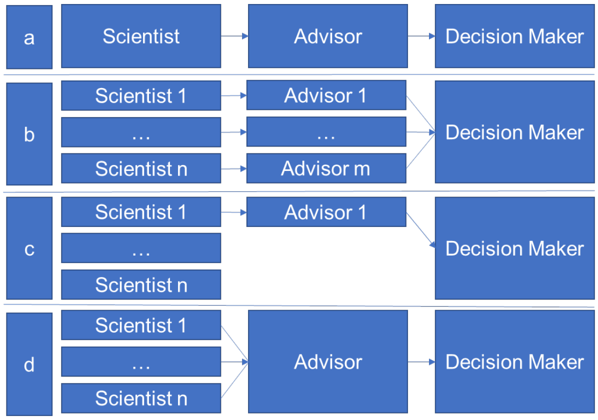

Figure 1: Role models in science-based decision making.

model b the decision maker is confronted with advice from multiple advisors. The pieces of advice might be conflicting and even mutually exclusive, which would be confusing.

Therefore, decision makers, at least in Germany, seem to prefer a heuristic approach, which is represented by model c. They focus on the first or most relevant advisor. The Advisor 1 in the pandemic is the domain of public health together with epidemiology and virology (Expertenrat 2021a, 2021b). In fact, the reality is mirrored by both models b and c with Advisor 1 being the controlling actor with their arguments based on incidence, hospitalization, or Intensive Care Unit utilization rates. Other disciplines act more as warning voices, setting boundary conditions to action lines (Leopoldina 2021).

SUITABILITY OF DECISION SUPPORT METHODS AND TOOLS

Scientific advice should treat the outcomes of natural and social sciences but also normative aspects from humanities, dealing e. g. with legal and ethical issues. Moreover, we expect that all arguments used are rational and based on evidence. Their connection to the given advice must be comprehensible and transparent. Furthermore, we would expect that all relevant evidence is considered. Taking the special circumstances of the pandemic into account, we require that the methods and tools can deal with volatility. That means that they are flexible and can be quickly adapted to match the needs of changing situations and boundary conditions. Updates shall handle new evidence, the credibility of sources and/or the reliability or maturity of knowledge. Finally, the advisors shall be able to express their own uncertainty concerning their advice and communicate the degree of freedom left to the decision makers.

In decision theory a variety of methods has been developed to support decisions. Due to requirement of rational decision support, we focus on the normative methods (Rapoport 1989) and consider Delphi Technique (Ngo et al. 2021; Tyrie et al. 2021), Scenario Technique (BMI 2020; Gausemeier et al.

Table 1. Estimated suitability of management methods for decision making in a pandemic on a 4-point scale (++,+,−,−−).

Requirement	Delphi Technique	Scenario Technique	Hierarchical Utility Analysis	Expected Utility Analysis
Handles interdisciplinary arguments	+	+	+	−
Handles normative (legal, ethical) aspects	+	+	−	−
Based on evidence and rationality	−	−	+	+
Comprehensible and transparent	+	+	−	−
Applicable under volatility	+	−	−	−
Simple and quick	+	+	−	− −
Handles reliability of evidence or credibility of sources	−	−	−	−
Updateable with new evidence	−	+	+	−
Communicates uncertainty of the result	+	+	−	−

2009), Deterministic Utility Analysis (Saaty 1996; Zangemeister 1970) and Expected Utility Analysis (Mongin and Baccelli 2020).

Table 1 provides an overview of the suitability of the instruments in a pandemic situation based on the above criteria in our view. The negative ratings might partly explain, why some of the methods are not used more frequently in the pandemic. They either do not meet the standards of a scientific advisor or cannot handle volatility and uncertainty. Most of them are not simple and quick. An exception is the Scenario Technique which scales from very quick and dirty to very elaborated and time-consuming processes, and the Delphi Technique, which has a good benefit-effort ratio. The others are less suited for ad hoc work as required in the volatile situation of the pandemic.

BAYESIAN SINGLE PASS REASONING

To better meet the above-mentioned requirements, we propose to use a method based on Bayesian reasoning (Bovens 2003) for ad hoc decision support. We target at the "probability that an action is the best among its alternatives" and call it "preferability". A preferability of 1 means a recommendation of the action with certainty. A preferability of 0 means a certain recommendation not to implement this action. Values in between express uncertainty. We accept the Bayesian understanding of probability as a degree of belief. This is realistic in a pandemic situation because we are lacking quantified interdisciplinary models that would allow for a frequentist view of probability throughout. But we propose to use frequencies instead of subjective estimates whenever they are available.

Instead of following the Delphi approach asking people directly for preferability we are using available evidence to estimate it. The calculus is given by

Bayes' theorem. Its ratio form for two alternative actions A and B is shown by Equations 1 and 2.

$$\frac{P(A|E_{i+1})}{P(B|E_{i+1})} = \frac{P(E_{i+1}|A)}{P(E_{i+1}|B)} \cdot \frac{P(A|E_i)}{P\,(B|E_i)} \tag{1}$$

$$P\left(A|E_{i+1}\right) + P\left(B\middle|E_{i+1}\right) = 1 \tag{2}$$

This means, that the ratio of preferabilities of alternative actions A and B is updated, under the condition that new evidence E_{i+1} is available, by multiplying the ratio of preferabilities of A and B under the old condition that only evidences E_1 thru E_i are available by the likelihood ratio (LR) of the new evidence E_{i+1}, under the condition that A or B are optimal (Equation 1). Equation 2 is a normalization condition, which allows for calculating preferabilities from the ratio. We propose to set the initial prior odd P(A)/P(B) before E_1 to 1, the uninformed prior, if no reliable prior evidence provides a better estimate.

We call this approach to decision making Bayesian Single Pass Reasoning (BSPR) because it is based on Bayesian reasoning and allows to evaluate the alternatives in a single pass in contrast to Expected Utility approaches that require both, utilities of alternatives and probabilities of futures.

The method requires the following steps:

1. Formulate the decision problem/question
2. Identify relevant alternative courses of actions
3. Collect all relevant pieces of evidence from all relevant disciplines
4. Group dependent pieces of evidence to formulate the set of independent E_i
5. Estimate the likelihood ratios for the E_i
6. Calculate preferabilities $P(A|E_i)$ and $P(B|E_i)$
7. Update with new evidence as it occurs

Step 3 avoids bias by cherry-picking of evidence. Step 4 prevents from repeated consideration of the same or very similar evidence in the calculation, which would also lead to bias. Steps 1 thru 4 and 7 can be also used as a checklist for the quality of the work of any scientific advisor.

DISCUSSION AND EXAMPLE

By design the method fulfils the requirements for scientific interdisciplinary advice in the pandemic: It is rational and based on evidence. It handles any type of evidence from any discipline. It is comparably simple and quick and thus comprehensible. It can be easily updated with new evidence. Credibility of the source and scientific reliability of the evidence are directly taken into account when estimating the likelihood ratios. BSPR allows to express uncertainty of results and to quantify it.

The order of the evidence is irrelevant for the BSPR updates. Therefore, evidence and their LRs should not change over the process of iterative updates. But Bayesian thinking accepts ignorance and even mistakes in its priors trusting that new evidence will correct the errors. However, sharp and rapid changes in the considered system will cause the updated preferability values to lag behind the situation in those cases. The underlying model of the analysis depends heavily on the selection and formulation of the evidence. The set of E_i represents the knowledge of the current situation and constitutes, together with implicit background knowledge, the world model for the decision. It will therefore have a big influence on the assessment of the likelihoods and thus the calculated preferability of potential actions.

But how will subjective estimates of the LR differ? We answer by way of an example. A student of technology management researched evidence for a lockdown measure in a student project for his thesis during the fourth wave of Covid-19 in Germany (Table 2). He set up a panel of 31 students of 9 nationalities at an average age of 25 (SD = 3.8 y). They rated independently the likelihoods of 17 arguments E_i in a questionnaire with respect to the alternative hypotheses A "lockdown essential to fight the pandemic" versus B "lockdown not necessary". A ten-point scale from 1 to 10 was used to rate likelihoods $P(E_i|A)$ and $P(E_i|B)$. Thus, $LR_i = P(E_i|A) : P(E_i|B)$ are restricted to the range 0.1 thru 10. The work took place during the rise of the fourth Covid-19 wave in late 2021.

The set of evidence consists of 17 elements and is interdisciplinary. The set is not exhaustive and was not approved by domain specialists. Some of the 10 arguments deal with the pandemic situation, 2 with social behavior, 1 is ethical, 2 are economic, and 2 name negative side effects on health. This means that more than half of the model is determined by the pandemic situation, while interdisciplinarity is respected. The overall likelihood ratios ($LR = \prod LR_i$) per participant differ considerably. This can be due to different views but also due to misunderstanding the concept of likelihood. The participants were asked for $P(E_i|A)$ and $P(E_i|B)$ but might have assessed $P(A|E_i)$ and $P(B|E_i)$ instead. Table 3 shows preferability statistics for all participants. On average the panel is not strictly decided (overall preferability $P = 0.67$). 48% of the participants rated in favor of a lockdown ($P > 0.95$), 23% against it ($P < 0.05$).

Decision makers, being aware of BSPR would insist on presenting more options of actions (Step 1 and 2). They would require more recent and more evidence to be considered by asking for additional evidence from domain experts (Step 3). They would ask a scientific advisor, whether the evidence is independent (Step 4). They would feel happy to receive interdisciplinary advice but would replace or amend the laymen panel with an expert panel (Step 5). They would insist on regular updates (Step 7) and perhaps require the implementation of a "dashboard" with regularly updated preferabilities as a basis for their decisions and for communicating the background of their decisions.

CONCLUSION AND OUTLOOK

We applied Bayesian reasoning to decision making in volatile and uncertain situations in a pandemic. We showed that the method fulfils requirements in such situations by design. We have demonstrated that it can be applied

Table 2. Average LR and standard deviation (SD) of Likelihood ratios of 17 pieces of evidence assessed by 31 persons for a lockdown.

#	Evidence/Argument (translated from German)	LR	SD
1	The easing policy was not conducive to epidemic control.	6.63	3.27
2	The epidemic fluctuated at a high level from mid-October to early December.	1.76	0.76
3	The number of new infections per day gradually declined after the December 3 lockdown.	5.51	3.09
4	Rapid tests are actually effective in only 58% of asymptomatic cases.	5.35	3.00
5	General vaccination has not yet started in Germany.	5.30	3.07
6	The human immune system is weaker in winter than in summer, making it susceptible to infection.	1.60	0.67
7	Covid-19 survives longer in cold conditions (temperature and UV exposure).	5.29	3.05
8	As Christmas approaches, the number of indoor parties will increase.	1.25	0.43
9	As the epidemic spreads, social consumption will shrink and food, tourism, cultural and economic activities will decline.	0.25	0.19
10	On March 3, the federal government started to loosen policies, and the number of new diagnoses rises again.	5.35	3.01
11	The majority of those infected have mild or no disease. The probability of survival for infected persons younger than 70 years is 99.95%.	0.26	0.16
12	The focus in the epidemic should be on protecting vulnerable people, not on equal distribution of medical resources.	0.65	0.28
13	The economic costs of mandatory blockade measures are far greater than the benefits of blockade.	0.24	0.17
14	The problem of failed and false viral tests on a large scale is common, resulting in the number of confirmed cases actually being higher.	2.24	2.00
15	Vacancies in buildings are increasing due to the advent of home-based work and schooling.	0.65	0.22
16	With the relaxation of measures and increased social interaction, people's impaired cognitive functions can be quickly restored.	0.19	0.13
17	The lives of millions of children are more exposed to the Internet, and therefore they are at increased risk of harm.	0.14	0.06

Table 3. Preferability P of a lockdown (N=31).

Average over all participants	0.67
Standard deviation	0.42
Share of participants with $P > 0.5$	0.71
Share of participants with $P > 0.95$	0.48
Share of participants with $P < 0.05$	0.23

to interdisciplinary decision-making using evidence and arguments from different kinds of sources.

BSPR shares epistemic shortcomings with other Bayesian applications. In particular, it is based on conditional independence of the evidence E_i, which is hard to prove in most cases. However, other rational decision approaches suffer from the same problem: they require independence of their decision criteria or orthogonality of their dimensions. We also share subjectivity with other methods in selecting the decision problem, choosing the alternative actions, and selecting and grouping evidence. In defense of the BSPR, we can say that we have this in common with most research and scientific work.

What hurts most from the perspective of an empirical scientist is the subjectivity of likelihoods. In this paper we focused on an example with subjective ratings of a non-representative panel. We ended up at least with a collective opinion and its dispersion, which is more than a single person's view. Expert panels should be addressed in further research to see if the ratings scatter less. Moreover, empirical scientists should consider providing decision makers with likelihoods based on data and simulation. What we got from simulation studies during the pandemic are scenarios and no probabilities or likelihoods. An objective for the future is switching to computed likelihoods based on data, grounded causal models, and simulation.

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