JUDICIAL AND CLINICAL DECISION MAKING UNDER UNCERTAINTY

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Abstract

Norms for judicial and clinical decisions under uncertainty differ. When clinicians are uncertain about patient health, they view the patient as a member of a population with similar attributes and make care decisions using available knowledge about the distribution of health in this population. In contrast, legal systems typically do not permit a defendant to be convicted of a crime based on a justification that persons with similar attributes often commit this crime. This paper examines the implications if, emulating clinical practice, judges making conviction decisions were to use knowledge of rates of crime commission.

Keywords: judges and clinicians, reasonable decisions under uncertainty, probability thresholds, frequentist and subjective probability

JEL Classifications: D81, K14, K40

1. Introduction

Judicial decision making in legal proceedings and clinical decision making in patient care differ in some ways and are alike in others. An obvious difference is that judicial settings are adversarial, while clinical ones aim to be collaborative. Plaintiffs and defendants typically have conflicting interests. Clinicians and patients ideally have congruent objectives.

Judicial and clinical decisions are alike in that both are made partially but not entirely on a case-by-case basis. Judges make case-specific decisions subject to mandated legal criteria and recommended guidelines. Clinicians make case-specific treatment decisions subject to medical criteria and guidelines. Thus, judges and clinicians exercise discretion subject to hard and soft constraints.

Judicial and clinical decisions are also alike in that both are commonly made with incomplete knowledge. Judges may be uncertain whether a defendant has committed a crime and what the consequences of alternative punishments would be. Clinicians may be uncertain whether a patient is ill and what the outcomes of alternative treatments would be.

There has been a striking contrast in the norms for judicial and clinical decision making under uncertainty. When clinicians are uncertain about the health and treatment response of a patient, they commonly view the patient as a member of a population with similar observed attributes. They make care decisions using available knowledge about the health status and treatment response of this population. A substantial research literature on evidence-based medicine presents the available knowledge in frequentist probabilistic terms.¹

Research on health risk assessment uses observational data to develop estimates of the frequency with which patients having specified attributes develop a disease of concern. Clinicians interpret frequentist risk assessments as probabilities for individual patients. Analyses of treatment response use randomized trials and observational data to estimate the population distribution of outcomes that would occur if all persons with specified attributes were to receive a specified treatment. Clinicians interpret the population outcome distribution as the distribution that an individual patient with these attributes should expect.

The quantitative social science literature on criminology and criminal justice policy operates in much the same way as does the research literature on evidence-based medicine. Criminologists use observational data to estimate the frequency with which persons having specified observed attributes commit crimes. Policy analysts use observational data and randomized trials to estimate the crime rates that would occur if a specified policing or sentencing policy were to be enacted, considering such frequentist implications as deterrence and incapacitation.

Yet social science research on criminal risk assessment and policy response is not used in judicial decision making in the manner that evidence-based medical research is used in clinical decision making. To the best of my knowledge, American and European legal systems ordinarily do not permit an individual to be

¹ By “frequentist,” I mean the frequency with which an event occurs in a population. Statistical theory often uses the word in a different way, indicating the frequency of occurrence of an event across repeated samples drawn randomly or in some other manner from a population.
convicted of a crime based on a frequentist justification that persons with similar observed attributes often commit this crime. To convict a defendant, a judge or jury must conclude that this individual committed a specific crime, meeting legal definitions of causation and intent in the case under consideration. It does not suffice to reason that persons like him often commit similar crimes.

Judges and juries are permitted to use probabilistic reasoning when they are uncertain whether defendants meet legal criteria for guilt. This is evident in legal use of terms such as “probable cause” and “balance of probabilities.” However, legal systems apply these terms in the Bayesian sense of a subjective probability of occurrence of an individual event, not in the frequentist sense of the prevalence of an event in a population. See, for example, Kaplan (1967).

This paper draws on some of my recent analysis of patient care under uncertainty to address broadly similar decision making in the criminal-justice system. Manski (2018a, 2018b, 2019) study choice between surveillance and aggressive treatment of a patient when a clinician is uncertain whether the patient is or will become ill. I first characterize optimal decision making with precise frequentist risk assessment and then consider criteria for reasonable decision making when research in evidence-based medicine enables partial frequentist assessment of risk of illness.

Judges and juries face an analogous problem of choice between finding a defendant guilty or not guilty when they are uncertain whether the defendant has committed the crime charged. They presently may approach this decision in a Bayesian subjective manner. Emulating the clinical use of research assessing frequentist risk of illness, legal systems could permit judges and juries to bring to bear research that assesses rates of crime commission.

I do not go so far as to argue outright that legal systems should permit judicial decisions to be made using frequentist information on rates of crime commission. I simply raise the possibility, having in mind that the prevailing subjective assessment of uncertainty in legal systems can itself be problematic. Judges and juries may vary in the accuracy of their subjective judgments. Hence, I think it warranted to consider frequentist assessment as a potentially more objective and uniform way to cope with uncertainty.

The analysis in the paper focuses on the decision of a judge to find a criminal defendant guilty. I consider a judge rather than a jury for simplicity. A judge is a single decision maker, whereas a jury is a group whose decision may reflect social interactions. The main themes of the paper also apply to jury decisions. They apply as well to judicial decisions regarding liability under tort law and to police decisions to search or arrest suspects.

Section 2 summarizes my earlier analysis of clinical decision making when a clinician can make a precise frequentist assessment of risk of disease for a patient with specified observed attributes. Section 3 considers the analogous judicial setting where a judge can precisely assess the relevant prevalence of crime commission. In both cases, the optimal decision rule is characterized by a case-specific threshold probability, whether of illness or crime commission. Aggressive

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2 A specific exception to this general statement may be the use of DNA evidence to identify offenders. DNA matching is frequentist, comparing the DNA profile of a suspected offender to the large set of profiles stored in a DNA database.
treatment (conviction) is optimal if the patient’s (defendant’s) probability of illness (crime commission) is above the threshold. Surveillance (a not-guilty finding) is optimal otherwise.

Section 4 addresses clinical and judicial decision making with partial knowledge of illness or crime rates. Partial rather than precise knowledge is realistic in practice. Optimization is not possible with partial knowledge, but decision theory offers various reasonable criterion for decision making. As I have done in many earlier studies of decision making under ambiguity, I compare outcomes using Bayesian, maximin, and minimax-regret criteria. Section 5 concludes.

Throughout this paper, my perspective on decision making is prescriptive rather than descriptive. Descriptive analysis seeks to understand and predict how actual decision makers behave. For example, it may study how actual physicians exercise “clinical judgment” and how judges use “intuition.” Prescriptive analysis seeks to improve decision making, formalizing broad ideas such as “optimal” and “reasonable” decisions.

2. Choice between Surveillance and Aggressive Treatment of a Patient at Risk of Disease

2.1. Background

A large class of clinical decisions chooses between surveillance and aggressive treatment of patients at risk of disease. A familiar example is choice between surveillance and drug treatment for patients at risk of heart disease or diabetes. A semantically distinct but equivalent decision is choice between diagnosis of patients as healthy or ill. Here the concern is not whether a patient will develop a disease in the future but whether the patient is currently ill.

The clinical decision commonly requires resolution of a tension between benefits and costs. Aggressive treatment may be more beneficial to the extent that it reduces the risk of disease development or the severity of disease that does develop. It may be more harmful to the extent that it generates health side effects and financial costs beyond those associated with surveillance.

Manski (2018a, 2018b, 2019) consider a simple but instructive version of the decision problem. I view it as a one-time choice rather than a dynamic decision that can be revisited and updated over time. I assume that treatment is individualistic, affecting the health of only the person treated. This assumption is generally realistic for non-infectious diseases, but it may not be appropriate for infectious diseases. Then treatment may have implications for spread of the disease.

Analysis is particularly simple when aggressive treatment affects disease in one of two polar ways. In one polar case, aggressive treatment prevents the occurrence of disease. In the other, it does not affect the occurrence of disease, but it reduces the severity of disease when it occurs. I focus here on the latter case, which is analogous to the judicial decision setting.

Section 2.2 shows that aggressive treatment is the better option if the probability of disease development exceeds a computable patient-specific threshold. Surveillance is the better option otherwise. The analysis in Section 2.2
considers an ideal situation where evidence-based medical research gives the clinician the precise frequentist probability of disease development for patients with specified observable attributes. In practice, research may yield only partial knowledge. I discuss such situations in Section 4.

2.2. Optimal Clinical Choice with Frequentist Risk Assessment

Here is a simple formalization of the problem of choice between surveillance and aggressive treatment using precise frequentist risk assessment. Let \( t = A \) denote surveillance and \( t = B \) denote aggressive treatment. Let \( y \) be a binary illness outcome, with \( y = 1 \) denoting that the patient has (or will develop) the disease under consideration and \( y = 0 \) otherwise. Let \( w \) denote the disease under consideration and let \( x \) be the patient attributes observed by a clinician. The analysis performed here assumes that the observable patient attributes are predetermined. Manski (2013) studies more complex settings in which clinicians may perform costly diagnostic tests in order to learn more about their patients.

Let \( P_{wx} = P(y = 1 | w, x) \) be the frequentist probability that a patient with observed attributes \( x \) has disease \( w \). In economics jargon, a clinician who knows \( P_{wx} \) is said to have rational expectations.

The utility of each care option depends on whether a patient develops the disease. Let \( u_{wx}(y, t) \) denote the expected utility of treatment \( t \) to a patient with attributes \( x \) in the presence of illness outcome \( y \). That expected utility may vary with \((w, x)\) as well as with \((y, t)\) is well-appreciated in modern clinical practice, which emphasizes the importance of “personalizing” patient care.

Suppose that the clinician must choose between \( A \) and \( B \) without knowing the illness outcome. The expected utility of each option \( t \) without knowledge of \( y \) is

\[
P_{wx} u_{wx}(1, t) + (1 - P_{wx}) u_{wx}(0, t).
\]

Maximization of expected utility yields the optimal treatment rule

\[
\text{Choose } A \text{ if } P_{wx} u_{wx}(1, A) + (1 - P_{wx}) u_{wx}(0, A) \geq P_{wx} u_{wx}(1, B) + (1 - P_{wx}) u_{wx}(0, B),
\]

\[
\text{Choose } B \text{ if } P_{wx} u_{wx}(1, B) + (1 - P_{wx}) u_{wx}(0, B) \geq P_{wx} u_{wx}(1, A) + (1 - P_{wx}) u_{wx}(0, A).
\]

A clinician who knows the relevant patient utility function and has rational expectations can implement the optimal treatment rule.

The optimal treatment depends on the magnitude of \( P_{wx} \) relative to the threshold value that equalizes the expected utility of the two treatments:

\[
P^*_{wx} = \frac{u_{wx}(0, A) - u_{wx}(0, B)}{[u_{wx}(0, A) - u_{wx}(0, B)] + [u_{wx}(1, B) - u_{wx}(1, A)]}.
\]
It often is reasonable to suppose that surveillance yields higher expected utility when a patient does not have the disease and that aggressive treatment yields higher utility when a patient does have the disease. That is, $u_{wx}(0, A) > u_{wx}(0, B)$, and $u_{wx}(1, B) > u_{wx}(1, A)$. Then $0 < P_{wx} < 1$. Treatment $A$ is optimal if $P_{wx} \leq P^*_{wx}$ and $B$ is optimal if $P_{wx} \geq P^*_{wx}$.

Threshold probability (3) has a simple interpretation. When a patient is not ill ($y = 0$), surveillance ($t = A$) is the better treatment. In this case, a clinician who chooses aggressive treatment ($t = B$) makes a Type I error and incurs a loss of magnitude $u_{wx}(0, A) - u_{wx}(0, B)$ relative to the optimum. Similarly, when a patient is ill ($y = 1$), aggressive treatment ($t = B$) is better. In this case, a clinician who chooses surveillance ($t = A$) makes a Type II error and incurs a loss of size $u_{wx}(1, B) - u_{wx}(1, A)$ relative to the optimum. Thus, the threshold probability for choice of aggressive treatment is the loss from a Type I error divided by the sum of the losses from Type I and Type II errors.

3. Choice Between Finding a Defendant Guilty or Not Guilty of a Crime

This section adapts the analysis of clinical choice between surveillance and aggressive treatment of patients to address judicial treatment of criminal defendants. Now the choice is to find a defendant guilty or not guilty of a crime. The defendant is analogous to the patient. A guilty decision is analogous to aggressive treatment, and a not-guilty one is analogous to surveillance. The assumption of individualistic treatment response made when considering patient care now means that the judicial decision made for one defendant does not affect judicial decision making or crime commission elsewhere. Uncertainty about whether a defendant committed the crime is analogous to uncertainty about whether a patient is ill. Section 3.1 provides the analysis and Section 3.2 discusses the finding.

3.1. Optimal Conviction Decisions with Frequentist Risk Assessment

Judicial and clinical decisions differ in that judges should aim to maximize social welfare rather than the private utility of patients. Nevertheless, the judicial choice problem has the same formal structure as the polar case of clinical choice in which aggressive treatment does not affect the occurrence of disease, but it reduces the severity of disease when it occurs. It is reasonable to assume that a guilty decision yields higher social welfare than a not-guilty one if the defendant committed the crime, but lower welfare if he did not. This is analogous to the assumption made earlier that aggressive treatment yields higher welfare than surveillance if a patient is ill, but lower welfare if the patient is healthy.

It may or may not be reasonable to assume that judicial decisions have only individualistic implications, analogous to medical treatment of non-infectious disease. Kaplow (2011) emphasizes that convictions may deter future crime, making judicial decisions similar to medical treatment of infectious disease. This warrants consideration, but I leave it aside here.
With these analogies to medical treatment, repetition of the analysis of Section 2.2 shows that finding a defendant guilty is the better choice if the probability of crime commission exceeds a computable defendant-specific threshold. A finding of not guilty is better otherwise.

Formally, let $t = A$ and $t = B$ now denote judicial decisions of not guilty and guilty. Let $y = 1$ if the defendant committed the crime charged and $y = 0$ otherwise. I take as given the prevailing legal criteria defining commission of a crime, including causation and intent. The important matter for my analysis is that judges commonly make conviction decisions while uncertain whether defendants satisfied the legal criteria for crime commission.

Let $w$ denote the crime charged and let $x$ be the defendant attributes observed by a judge. In practice, $x$ is determined by the information that prosecutors, defense attorneys, and witnesses provide at trials. Let $P(w, x) = P(y = 1 | w, x)$ be the frequentist probability that defendants with observed attributes $x$ commit crime $w$. Let $u_w(y, t)$ denote the social welfare of making decision $t$ for a defendant with attributes $x$ in the presence of crime outcome $y$.

I do not specify exactly how society evaluates welfare, as expressed through $u_w(y, t)$. However, I think it reasonable to assume that two inequalities hold. Specifically, a guilty decision yields higher social welfare than a not-guilty one if the defendant committed the crime, but it yields lower welfare if he did not. That is, $u_w(0, A) > u_w(0, B)$ and $u_w(1, B) > u_w(1, A)$. These inequalities are analogous to those assumed earlier in the analysis of clinical decisions.

With these assumptions, the earlier finding on optimal clinical decisions holds for judicial decisions. The threshold probability $P^*_w$ defined in (3) lies in the interval $(0, 1)$. Decision $A$ is optimal if $P_w \leq P^*_w$ and $B$ is optimal if $P_w \geq P^*_w$.

3.2. Discussion

Analysis of optimal judicial decision making in the above manner has precedent in legal scholarship. Indeed, a threshold probability for conviction essentially equivalent to (3) appears in the literature as early as Kaplan (1967); see Section IIB. However, Kaplan is adamant that probability should be conceptualized in subjective rather than frequentist terms. A recent study providing related analysis is Burtis, Gelbach, and Kobayashi (2018).

The prevailing legal criterion for dealing with uncertainty when deciding whether to convict a criminal defendant is that the person should be guilty “beyond a reasonable doubt.” Blackstone (1769) gave a particularly famous quantification, remarking that “It is better that ten guilty persons escape than that one innocent suffer.” Earlier, Hale (1736) wrote “it is better five guilty persons should escape unpunished, than one innocent person should die.” Centuries earlier still, Maimonides wrote “It is better and more satisfactory to acquit a thousand guilty persons than to put a single innocent man to death once;” see Chavell (1967).

These declarations suggest a welfare evaluation that the loss to society when convicting a defendant who did not commit a crime (a Type I error) is ten or five or a thousand times the loss when not convicting a defendant who did commit a crime (a Type II error). Applying them to the above analysis implies that the threshold probability for conviction should be $10/11$ or $5/6$ or $1000/1001$. 
Use of one of these or another quantitative interpretation of “beyond a reasonable doubt” is consistent with the optimization analysis of Section 3.1. However, each interpretation renders the threshold probability for conviction invariant across crime types \( w \) and defendant attributes \( x \). In terms of our analysis, each assumes that the relative losses to society associated with Type I and Type II errors does not vary with \((w, x)\).

With a few exceptions, the literature in criminal law does not motivate this invariance assumption. I think it highly plausible that society may want to evaluate the relative losses of Type I and II errors differently for different crime types. The evaluation might vary with the severity of the crime and with the nature of the sentences received by convicted defendants. It is also conceivable that society may want to evaluate losses from errors in a manner that varies with certain defendant attributes.

Among the few authors who question the invariance assumption, Kaplan (1967) does so at length and persuasively. More recently, Epps (2015) has observed that the quantifications asserted by Maimonides, Hale, and Blackstone were offered in a historical context where numerous crimes, including ones that are considered minor today, were punished exclusively by execution of the convicted person. Epps argues that these quantifications should not be used in the modern context, where capital punishment has become very rare. Epps also suggests that criteria for conviction decisions should vary across crimes because (p. 1091): “the costs of false acquittals . . . . likely vary significantly among crimes.”

4. Decision Making with Partial Frequentist Risk Assessment

The optimization analysis of Sections 2 and 3 presumed that the decision maker, whether clinician or judge, knows the frequentist outcome probability \( P_{wx} \) and the relevant utility or welfare function \( u_{wx}(\cdot, \cdot) \). The only uncertainty was the value \( y \) of the illness or crime outcome for the patient or defendant under consideration. In practice, a decision maker may have to act with incomplete knowledge of \( P_{wx} \) or \( u_{wx}(\cdot, \cdot) \). Manski (2018a, 2018b, 2019) has studied clinical decision making in a relatively simple setting where the clinician has incomplete knowledge of \( P_{wx} \) but complete knowledge \( u_{wx}(\cdot, \cdot) \). I summarize in Section 4.1 and consider judicial decision making in Section 4.2.

4.1. Clinical Choice

Suppose that a clinician does not know \( P_{wx} \) precisely, but he can use available evidence and credible assumptions to conclude that \( P_{wx} \in [P_{wxL}, P_{wxH}] \), where \( P_{wxL} \) and \( P_{wxH} \) are known lower and upper bounds on the probability of illness. My studies of patient care under uncertainty show that precise knowledge of frequentist illness probabilities is rare in practice, but partial knowledge may be realistic.

Partial knowledge is unproblematic for decision making if \( P^*_{wx} \) is not inside the interval \([P_{wxL}, P_{wxH}]\). Choosing \( t = A \) is sure to be optimal if \( P_{wxH} \leq P^*_{wx} \) and choosing \( t = B \) is sure to be optimal if \( P^*_{wx} \leq P_{wxL} \). However, there exists no
definitely optimal treatment if $P^*_{wx}$ is within $[P_{wxL}, P_{wxH}]$. Then there exist feasible values of $P_{wx}$ that make only $A$ optimal and other values that make only $B$ optimal. I henceforth focus on this situation.

The Bayesian prescription for decision making places a subjective distribution on $P_{wx}$ and maximizes subjective expected utility. Let $\pi_{wx}$ denote the subjective mean that a Bayesian clinician holds for $P_{wx}$. A Bayesian clinician acts as if $P_{wx} = \pi_{wx}$. That is, he finds it subjectively optimal to choose treatment $A$ if $\pi_{wx} \leq P^*_{wx}$ and $B$ if $P^*_{wx} \leq \pi_{wx}$.

The Bayesian perspective is compelling if one feels able to place a credible subjective distribution on the probability of illness. However, a subjective distribution is a form of knowledge, and a decision maker may not feel able to assert one. Bayesians have long struggled to provide guidance and the matter continues to be controversial.

When one finds it difficult to assert a credible subjective distribution, a reasonable way to act is to use a decision criterion that achieves uniformly satisfactory results, whatever the actual illness probability may be. Using the language of decision theory, I shall say that a possible value for the actual illness probability is a possible “state of nature.” There are multiple ways to formalize the idea of uniformly satisfactory results. The two most commonly studied are the maximin and minimax-regret (MR) criteria.

The maximin criterion chooses an action that maximizes the minimum welfare that might possibly occur. The minimax-regret criterion considers each state of nature and computes the loss in welfare that would occur if one were to choose a specified action rather than the one that is best in this state. This quantity, called regret, measures the nearness to optimality of the specified action in the state of nature. The decision maker must choose without knowing the true state. To achieve a uniformly satisfactory result, he computes the maximum regret of each action; that is, the maximum distance from optimality that the action would yield across all possible states of nature. The MR criterion chooses an action that minimizes this maximum distance from optimality.

In the analytical setting of Section 2, the maximin decision is simple to derive if being healthy is better than being ill, regardless of which treatment a patient receives. Thus, suppose that $u_{wx}(0, A) > u_{wx}(1, A)$ and $u_{wx}(0, B) > u_{wx}(1, B)$. Then the worst feasible expected utilities under options $A$ and $B$ both occur when $P_{wx}$ equals its upper bound $P_{wxH}$. Hence, the clinician acts as if $P_{wx} = P_{wxH}$. The maximin choice is $A$ if $P_{wxL} \leq P^*_{wx}$ and $B$ if $P_{wxH} \geq P^*_{wx}$.

The minimax-regret criterion evaluates each action by the worst reduction in expected utility that it may yield relative to the highest expected utility achievable. Let $P_{wxM}$ denote the midpoint of the interval $[P_{wxL}, P_{wxH}]$. Manski (2018a) shows that the minimax-regret choice is the same as a clinician maximizing expected utility would make if he were to know that $P_{wx} = P_{wxM}$.

Observe that, in the setting studied here, the maximin choice is the same that a Bayesian clinician would make if he were to place subjective probability one on $P_{wxH}$. The minimax-regret criterion is the same that a Bayesian clinician would make if he were to place any symmetric subjective distribution on the interval $[P_{wxL}, P_{wxH}]$. 
4.2. Judicial Choice

Now consider a judge who does not know $P_{wx}$ precisely. I expect this to be the prevalent judicial situation in practice.

One might conjecture that observation of conviction rates for defendants with attributes $x$ who are indicted for crime $w$ would reveal $P_{wx}$. However, conviction rates do not, in general, equal rates of crime commission. If judges could optimize in the manner of Section 3, the conviction rate conditional on $(w, x)$ would equal one when $P_{wx} > P^*_{wx}$ and zero when $P_{wx} < P^*_{wx}$. If judges lack the information to optimize, the relationship between conviction rates and rates of crime commission depends on how judges behave when making decisions under uncertainty.

As in Section 4.1, suppose that a judge can use available evidence and credible assumptions to conclude that $P_{wx} \in [P_{wxL}, P_{wxH}]$, where $P_{wxL}$ and $P_{wxH}$ are known lower and upper bounds. Then a judge might, analogously to a clinician, make a Bayesian, maximin, or minimax-regret decision. As far as I am aware, the literature on judicial procedure does not provide guidance on how a judge should behave. Section 4.1 makes clear that the criterion used is consequential. Hence, I recommend that legal scholars consider the matter seriously.

5. Conclusion

Use of frequentist risk assessment in clinical decision making is routine and widely accepted. This is not so in judicial decision making and I expect that it may be controversial. Some members of the legal community may reject it out of hand on deontological grounds. Before doing so, I would ask legal scholars and jurists to keep in mind that the alternative of purely subjective assessment is itself problematic. The long-accepted criterion that a defendant should be guilty “beyond a reasonable doubt” is vague. It does not ensure that judicial decision making under uncertainty will be objective or uniform.

This paper has put forward a second theme that I think warrants attention regardless of whether judges perform frequentist or subjective risk assessment. This is that the level of certainty that society seeks when convicting criminal defendants may in principle vary with the type of crime and the attributes of the defendant. The analysis in the paper formalizes this idea in a simple manner, expressing it through the threshold probability $P^*_{wx}$. 
References


Hale, Matthew (1736), Historia Placitorum Coronæ: The History of The Pleas of The Crown, republished in 2004 by The Lawbook Exchange, Clark, NJ.


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