Gregory Wheeler and William Harper
edited by
Henry E. Kyburg, Jr.

Essays in Honour of

Interference and
Probability
Bayesian apple

Forbidden Fruit: When Epistemological
awareness may not take a bite of the

Terry Sanford

Page 1
\[
\frac{\partial}{\partial x} (f(x)g(x)) = f(x) \frac{\partial g(x)}{\partial x} + g(x) \frac{\partial f(x)}{\partial x}
\]

(2) Let's consider the derivative of the product of two functions, \( f(x)g(x) \). According to the product rule of differentiation, the derivative is given by:

\[
\frac{d}{dx} (f(x)g(x)) = f(x) \frac{d}{dx} g(x) + g(x) \frac{d}{dx} f(x)
\]

In natural language:

The derivative of the product of two functions, \( f(x)g(x) \), is the product of the first function and the derivative of the second, plus the product of the second function and the derivative of the first. This formula can be applied to find the rate of change of the product of two functions with respect to a variable.
positive, expected information gain in going from the prior to the posterior is directly
related to producing information, as measured by a commonly used metric, the
Kullback-Leibler divergence, with respect to the posterior. If and only if
\( d(x) \) \((x)_{d} \) \[ \log_{2} \sum d(x) \] is
finite, this divergence is (i.e., there is no information gained in going from the prior

\[ \text{KL}(\text{posterior} | \text{prior}) = \sum \text{(posterior) \log \left( \frac{\text{(posterior)}}{\text{(prior)}} \right)} \]

a space \( C \) is Kullback-Leibler information
A familiar likelihood-based measure of information that measures how much
information that were it learned, would change the interpretation's

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and some of is
3. When Epistemological Probability may not go Bayesian

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though I have never heard the decision theory that goes together with the theory of indeterministic probabilities, it should not be surprising to learn that these theories are not even within our scope.

In [Section 4], we show that only the density-facts do not enter the decision theory of indeterministic probabilities, and that the decision theory of indeterministic probabilities is unnecessary for any model for indeterministic probabilities. Moreover, new methods of conditioning probabilities to new events do not enter the decision theory of indeterministic probabilities, and that the decision theory of indeterministic probabilities is unnecessary for any model for indeterministic probabilities. Moreover, new methods of conditioning probabilities to new events do not enter the decision theory of indeterministic probabilities.

This, then, is how the conditional probability for event E is defined. Since E has only one occurrence, we define its probability as the probability of E given E.

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and

\[ P(E|E') = P(E) \]

for any event E.

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