PME are unlikely to subscribe to these conditions, the position of PME in the larger debate over inductive logic and reasoning is not undermined.

In Section 2, I will introduce the obverse Majerník problem and sketch how it ties in with two natural generalizations of Jeffrey conditioning: Wagner conditioning and the PME. In Section 3, I will introduce Jeffrey conditioning in a notation that will later help us to solve the obverse Majerník problem. In Section 4, I will introduce Wagner conditioning and show how it naturally generalizes Jeffrey conditioning. In Section 5, I will show that PME does so as well under conditions that are straightforward to accept for proponents of PME. This solves the obverse Majerník problem and makes Wagner conditioning unnecessary as a generalization of Jeffrey conditioning, since the PME seamlessly incorporates it. The conclusion in Section 6 summarizes my claims and briefly refers to epistemological consequences. An appendix gives proofs how PME generalizes standard conditioning and Jeffrey conditioning, providing a template for a simplified proof of the claim in the body of the paper.

2. Jeffrey's Updating Principle and the Principle of Maximum Entropy

In his paper "Marginal Probability Distribution Determined by the Maximum Entropy Method" (see [2]), Vladimír Majerník asks the following question: If we had two partitions of an event space and knew all the conditional probabilities (any conditional probability of one event in the first partition conditional on another event in the second partition), would we be able to calculate the marginal probabilities for the two partitions? The answer is yes, if we commit ourselves to PME:

> [PME] Keep the information entropy of your probability distribution maximal within the constraints that the evidence provides (in the synchronic case), or your cross-entropy minimal (in the diachronic case).

For Majerník's question, PME provides us with a unique and plausible answer (see Majerník's paper). We may also be interested in the obverse question: if the marginal probabilities of the two partitions were given, would we similarly be able to calculate the conditional probabilities? The answer is yes: given PME, Theorems 2.2.1. and 2.6.5. in [3] reveal that the joint probabilities are the product of the marginal probabilities (see also [4]). Once the joint probabilities and the marginal probabilities are available, it is trivial to calculate the conditional probabilities.

It is important to note that these joint probabilities do not legislate independence, even though they allow it [4] (p.1670). Mérouane Debbah and Ralf Müller correctly describe these joint probabilities as a model with as many degrees of freedom as possible, which leaves free degrees for correlation to exist or not [4] (p.1674). This avoids the introduction of unjustified information [4] (p.1672) corresponding to the simple intuition behind PME: when updating your probabilities, waste no useful information and do not gain information unless the evidence compels you to gain it (see [4] (p.1685f), [5] (p.376), [6,7], [8] (p.186)). The principle comes with its own formal apparatus, not unlike probability theory itself: Shannon's information entropy [9], the Kullback-Leibler divergence (see [10,11], [12] (p.308ff), [13] (p.262ff)), the use of Lagrange multipliers (see [3] (p.409ff), [12] (p.327f), [13] (p.281)), and the log-inverse relationship between information and probability (see [14–17]).

There is an older problem by Carl Wagner [18] which can be cast in similar terms as Majerník's. If we were given some of the marginal probabilities in an updating problem as well as some logical relationships between the two partitions, would we be able to calculate the remaining marginal