

# A Bayesian Petrophysical Decision Support System for Estimation of Reservoir Compositions

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## Abstract

In this paper we describe a Bayesian approach for obtaining compositional estimates that combines expert knowledge with information obtained from measurements. We define a prior model for the compositional volume fractions and observation models for each of the measurement tools. Both prior and observation models are based on domain expertise. These models are combined in a joint probability model. To deal with the nonlinearities in the model, Bayesian inference is implemented by using the hybrid Monte Carlo algorithm.

## 1 Introduction

In this paper[1] we describe a Bayesian net for the estimation of compositional volume fractions in a hydrocarbon reservoir on the basis of logging data. It is an extension of the work described in Spalburg [2].

## 2 Probabilistic modeling

The starting point is a model for the probability distribution  $P(\vec{v}, \vec{m})$  of the compositional volume fractions  $\vec{v}$  and borehole measurements  $\vec{m}$ . A causal argument “*The composition is given by the (unknown) volume fractions, and the volume fractions determine the distribution measurement outcomes of each of the tools*” leads us to a Bayesian net formulation of the probabilistic model,

$$P(\vec{v}, \vec{m}) = \prod_{i=1}^Z P(m_i | \vec{v}) P(\vec{v}).$$

In this model,  $P(\vec{v})$  is the prior probability distribution of volume fractions before having seen any data. The factor  $\prod_{i=1}^Z P(m_i | \vec{v})$  is the *observation model*. The observation model relates volume fractions  $\vec{v}$  to measurement outcomes  $m_i$  of each of the  $Z$  tools  $i$ . Now given a set of measurement outcomes  $\vec{m}^o$ , the probability distribution of the volume fractions can be updated by applying *Bayes' rule*,

$$P(\vec{v} | \vec{m}^o) = \frac{\prod_{i \in Obs} P(m_i^o | \vec{v}) P(\vec{v})}{P(\vec{m}^o)}. \quad (1)$$

The observation model models our belief in the outcome of the measurements  $\vec{m} \in \mathbb{R}^Z$  given the actual composition  $\vec{v}$  of the reservoir. For each of the measurement tools, we assume additive Gaussian distributed measurement noise, i.e.  $m_j = f_j(\vec{v}) + \xi_j$ . The real valued functions  $f_j$  are the deterministic tool values [2].

### 2.1 Bayesian inference

In addition to these real valued functions we provide a set of observations  $\{m_i^o\}, i \in Obs$ , to compute the posterior distribution. If we were able to find an expression for the evidence term, i.e. for the marginal

distribution of the observations  $P(\vec{m}^o) = \int_{\vec{v}} \prod_{i \in \text{Obs}} P(m_i^o | \vec{v}) P(\vec{v}) d\vec{v}$  then the posterior distribution (1) could be written in closed form and readily evaluated. Unfortunately  $P(\vec{m}^o)$  is intractable and a closed-form expression does not exist. In order to obtain the desired compositional estimates we therefore have to resort to sampling methods. In our application we use the hybrid Monte Carlo (HMC) sampling algorithm. HMC is a powerful class of MCMC methods that are designed for problems with continuous state spaces, such as we consider in this paper.

### 3 Simulations

We looked at the ability of the system to estimate the composition of a (synthetic) reservoir and the ability to reproduce the results. The estimates are within one error bar from the actual composition. A notable exception occurs when of quartz or dolomite is present. This is caused by the fact that the tools employed are incapable of distinguishing between these minerals; during sampling possible states are visited alternatively (figure 1 left). When no measurement data is available, the samples follow the prior distribution (figure 1 right).

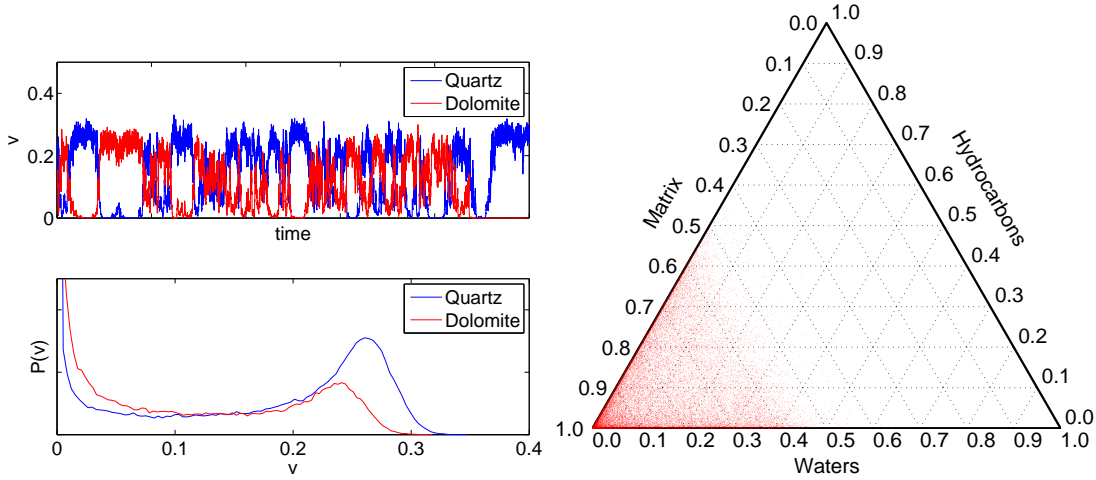


Figure 1: Diagrams for quartz and dolomite. Left top: time traces showing the mutually exclusive behavior, left-bottom: resulting multimodal probability distribution. The two peaks indicate the two main states, the valley corresponds to transient behavior between those two states. Right: Likely compositions when only the prior is known.

Results of simulations with other measurement values of (not reported here) confirm that the sampler generates reproducible results, consistent with the underlying compositional vector.

### 4 Discussion

This research has demonstrated a model and methodology for obtaining compositional estimates given some (or none) observations combined with expert knowledge. The ability of the system to estimate compositions is tested using synthetic data. The estimates are within one error bar (uncertainty bound) from the actual value for unimodal distributions. Tests also confirmed that the method is consistent, different simulations result in the approximately the same estimates with only minor differences.

### References

- [1] Burgers, W., Wiegerinck, W., Kappen, B., Spalburg, M. *A Bayesian Petrophysical Decision Support System for Estimation of Reservoir Compositions*. Expert Systems With Applications, in press, 2010 1988.
- [2] M.R. Spalburg. Bayesian uncertainty reduction for log evaluation. *SPE International*, October 2004. SPE88685.