

# Hidden Markov Models

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## 1 Introduction

Hidden Markov Models (HMMs) represent a class of models that provide a convenient (and often necessary) mechanism of integrating measurement and observation noise/errors into the scope of a theoretical description. HMMs have found an tremendous level of applicability to many problems in the world of information theory, signal processing, as well as—more recently—within the machine learning/artificial intelligence community. Concretely, a hidden markov model is just a probabilistic function of a Markov model, through a discrete, memoryless observation channel. Put more simply, the underlying model (whatever that may be) is assumed to be Markovian, but the observation channel translates that Markovian process into an output (or observation) sequence that contains some amount of noise.

## 2 Discrete State Markov Models

## 3 Hidden Markov Models

### 3.1 Bayesian Filtering

### 3.2 Backward Algorithm

### 3.3 Bayesian Smoothing

## 4 Parameter Inference

### 4.1 Likelihood Maximization

### 4.2 Baum-Welch Rearameterization

## 5 Discussion

## 6 Conclusions