

# Artificial Intelligence: A Probabilistic Machine Learning

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## Introduction

In 1950, Alan Turing was a milestone in the field of modern computers and artificial intelligence. The “Turing test” was founded on the idea that a computer’s intelligence is defined by its ability to perform at a human level in cognition-related tasks. AI created a surge of interest in the 1980s and 1990s. In the world of healthcare, artificial intelligence methodologies such as fuzzy expert systems, Bayesian networks, artificial neural networks, and hybrid intelligent systems have been applied in a variety of clinical contexts. When compared to other areas, healthcare applications earned the most investments in AI research in 2016. Learning can be thought of as inferring reasonable models to explain observed data, which is the core notion underpinning the probabilistic framework for machine learning. Such models can be used by a machine to generate predictions about future data and create rational judgments based on those predictions. Uncertainty is a major factor in all of this. Observed data can be compatible with a variety of models, making it difficult to determine which model is best suited to the data. Predictions concerning future data and the effects of actions are also unreliable. The framework for modeling uncertainty is provided by probability theory.

The appropriate probabilistic representation of uncertainty is essential to many elements of learning and intelligence. Probabilistic techniques to artificial intelligence, robotics, and machine learning have just lately become mainstream. Even now, there remains debate over how crucial it is to accurately reflect uncertainty in these disciplines. Advances in leveraging deep neural networks to address difficult pattern-recognition problems like speech recognition, image classification and text word prediction, for example, do not openly convey the uncertainty in the structure or parameters of those neural networks. However, my focus will be on issues in which uncertainty is a fundamental factor, rather than on pattern-recognition problems typified by the availability of enormous volumes of data.

All forms of uncertainty are expressed using probability theory in the probabilistic approach to modelling. In the same way that calculus is the dialect for representing and manipulating rates of change, probability theory is the mathematical framework for representing and managing uncertainty. Fortunately, the probabilistic approach to modelling is conceptually very simple: probability distributions are used to represent all of the uncertain unobserved quantities in a model (including structural, parametric, and noise-related) and how they relate to the data using probability distributions. The unobserved values are then inferred using fundamental probability theory rules based on the available data. The translation of prior probability distributions (specified before witnessing the data) into posterior distributions is used to learn from data (after observing data).

Because it is a normative theory for learning in artificially intelligent systems, probabilistic modelling offers several conceptual advantages over alternatives. In light of data, how should an artificially intelligent system describe and update its opinions about the world, etc. The Cox axioms establish some desiderata for describing beliefs; as a result, ‘degrees of belief,’ ranging from ‘impossible’ to ‘absolutely certain,’ must adhere to all probability theory laws. In artificial intelligence, this justifies the use of subjective Bayesian probabilistic representations. Probabilistic approaches to machine learning and intelligence are a burgeoning field of study with far-reaching repercussions beyond pattern recognition. Data compression, optimization, decision making, scientific model finding and interpretation, and personalization are only a few of the issues I’ve mentioned. The main difference between issues that require a probabilistic approach and those that can be handled using non-probabilistic machine-learning methodologies is whether or not uncertainty plays a significant role. Furthermore, most traditional optimization-based machine-learning algorithms have probabilistic equivalents that handle uncertainty more logically.

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## Conflict of Interest Statement

Authors declare they have no conflict of interest with this manuscript.

