results established in a famous correspondence between Blaise Pascal and Pierre de Fermat in 1654. As with probability itself, the results were initially motivated by gambling problems (see Exercise 13.9). The first published textbook on probability was *De Ratiociniis in Ludo Aleae* (Huygens, 1657). The "irrational and ignorance" view of uncertainty was described by John Arbuthnot in the preface of his translation of Huygens (Arbuthnot, 1692): "It is impossible for a Die, with such determin'd force and direction, not to fall on such determin'd side, only I don't know the force and direction which makes it fall on such determin'd side. and therefore I call it Chance, which is nothing but the want of art..."

Laplace (1816) gave an exceptionally accurate and modern overview of probability; he was the first to use the example "take two urns, A and B, the first containing four white and two black balls, ..." The Rev. Thomas Bayes (1702-1761) introduced the rule for reasoning about conditional probabilities that was named after him (Bayes, 1763). Bayes only considered the case of uniform priors; it was Laplace who independently developed the general case. Kolmogorov (1950, first published in German in 1933) presented probability theory in a rigorously axiomatic framework for the first time. Rényi (1970) later gave an axiomatic presentation that took conditional probability, rather than absolute probability, as primitive.

Pascal used probability in ways that required both the objective interpretation, as a property of the world based on symmetry or relative frequency. and the subjective interpretation, based on degree of belief—the former in his analyses of probabilities in games of chance, the latter in the famous "Pascal's wager" argument about the possible existence of God. However, Pascal did not clearly realize the distinction between these two interpretations. The distinction was first drawn clearly by James Bernoulli (1654-1705).

Leibniz introduced the "classical" notion of probability as a proportion of enumerated, equally probable cases, which was also used by Bernoulli, although it was brought to prominence by Laplace (1749-1827). This notion is ambiguous between the frequency interpretation and the subjective interpretation. The cases can be thought to he equally probable either because of a natural, physical symmetry between them, or simply because we do not have any knowledge that would lead us to consider one more probable than another. The use of this latter, subjective consideration to justify assigning equal probabilities is known as the principle of indifference. The principle is often attributed to Laplace, but he never isolated the principle explicitly. George Boole and John Venn both referred to it as the principle of insufficient reason; the modern name is due to Keynes (1921).

The debate between objectivists and subjectivists became sharper in the 20th century. Kolmogorov (1963), R. A. Fisher (1922), and Richard von Mises (1928) were advocates of the relative frequency interpretation. Karl Popper's (1959, first published in German in 1934) "propensity" interpretation traces relative frequencies to an underlying physical symmetry. Frank Ramsey (1931), Bruno de Finetti (1937), R. T. Cox (1946), Leonard Savage (1954), Richard Jeffrey (1983), and E. T. Jaynes (2003) interpreted probabilities as the degrees of belief of specific individuals. Their analyses of degree of belief were closely tied to utilities and to behavior—specifically, to the willingness to place bets. Rudolf Carnap, following Leibniz and Laplace, offered a different kind of subjective interpretation of probability—not as any actual individual's degree of belief, but as the degree of belief that an idealized individual *should* have in a particular proposition a, given a particular body of evidence e.
Catnap attempted to go further than Leibniz or Laplace by making this notion of degree of confirmation mathematically precise, as a logical relation between a and e. The study of this relation was intended to constitute a mathematical discipline called inductive logic, analogous to ordinary deductive logic (Catnap, 1948, 1950). Catnap was not able to extend his inductive logic much beyond the propositional case, and Putnam (1963) showed by adversarial arguments that some fundamental difficulties would prevent a strict extension to languages capable of expressing arithmetic.

Cox’s theorem (1946) shows that any system for uncertain reasoning that meets his set of assumptions is equivalent to probability theory. This gave renewed confidence to those who already favored probability, but others were not convinced, pointing to the assumptions (primarily that belief must be represented by a single number, and thus the belief in must be a function of the belief in p). Halpern (1999) describes the assumptions and shows some gaps in Cox’s original formulation. Hum (2003) shows how to patch up the difficulties. Jaynes (2003) has a similar argument that is easier to read.

The question of reference classes is closely tied to the attempt to find an inductive logic. The approach of choosing the "most specific" reference class of sufficient size was formally proposed by Reichenbach (1949). Various attempts have been made, notably by Henry Kyburg (1977, 1983), to formulate more sophisticated policies in order to avoid some obvious fallacies that arise with Reichenbach’s rule, but such approaches remain somewhat ad hoc. More recent work by Bacchus, Grove, Halpern, and Koller (1992) extends Carnap’s methods to first-order theories, thereby avoiding many of the difficulties associated with the straightforward reference-class method. Kyburg and Teng (2006) contrast probabilistic inference with nonmonotonic logic.

Bayesian probabilistic reasoning has been used in AI since the 1960s, especially in medical diagnosis. It was used not only to make a diagnosis from available evidence, but also to select further questions and tests by using the theory of information value (Section 16.6) when available evidence was inconclusive (Corry, 1968; Corry et al., 1973). One system outperformed human experts in the diagnosis of acute abdominal illnesses (de Dombal et al., 1974). Lucas et al. (2004) give an overview. These early Bayesian systems suffered from a number of problems, however. Because they lacked any theoretical model of the conditions they were diagnosing, they were vulnerable to unrepresentative data occurring in situations for which only a small sample was available (de Dombal et al., 1981). Even more fundamentally, because they lacked a concise formalism (such as the one to be described in Chapter 14) for representing and using conditional independence information, they depended on the acquisition, storage, and processing of enormous tables of probabilistic data. Because of these difficulties, probabilistic methods for coping with uncertainty fell out of favor in AI from the 1970s to the mid-1980s. Developments since the late 1980s are described in the next chapter.

The naive Bayes model for joint distributions has been studied extensively in the pattern recognition literature since the 1950s (Duda and Hart, 1973). It has also been used, often unwittingly, in information retrieval. beginning with the work of Maron (1961). The probabilistic foundations of this technique, described further in Exercise 13.22, were elucidated by Robertson and Sparck Jones (1976). Domingos and Pazzani (1997) provide an explanation.