Firstly, we address the screening problem where an item is declared to be good if certain of its characteristics $\mathbf{y}$ lie within a specified set. Often, these criterion variables cannot be measured without damaging the object. The characteristics of an experimental unit are partitioned into criterion variables, $\mathbf{Y}$, and covariates, $\mathbf{X}$, useful for screening. We develop a Bayes screening procedure based on a training set of data which includes the values of both $\mathbf{X}$ and $\mathbf{Y}$. For a future unit, only $\mathbf{X}$ will be observed. Our decision theory approach integrates all of the components (1) misclassification costs (2) conditional densities of the $\mathbf{X}$ and $\mathbf{Y}$, given the parameters, and (3) a prior distribution. It establishes that the Bayes rule is based on the predictive distribution. We generalize the result to the case of screening into m classes. A bivariate normal example illustrates the point that extreme values for the ratio of misclassification costs can produce Bayes rules where the objects are always called good whatever the values of the covariates.

Secondly, we address the classification problem. Again using a decision approach, we derive an alternative to the classical classification rule by allowing the parameters of the underlying distributions to be generated from a prior distribution. The Bayes rule is then extended to the m-population classification problem.

We derive an asymptotic expansion of the predictive distribution where the coefficients of powers of n^{-1} remain uniformly bounded in n when they are integrated over the entire sample space. Using the result for a first order expansion of the predictive density, we obtain asymptotic bounds for the Bayes risk in both the classification and the screening problems.