3. **Performance aspect:**

   **Purpose:**
   Predict the future payment behavior of the existing debtors to isolate problem ones, to which more attention and assistance can be devoted, thereby reducing the likelihood that these debtors will become a problem.

   **Example:**
   Behavior scoring: Scoring models that evaluate the risk levels of existing debtors.

4. **Bad debt management:**

   **Purpose:**
   Select optimal collections policies to minimize the cost of administering collections or maximizing the amount recovered from the delinquents’ account.

   **Example:**
   Scoring models for collection decisions: Scoring models that decide when actions should be taken on the accounts of delinquents and which of several alternative collection techniques might be more appropriate and successful.

The overall objective of credit scoring is not only to determine whether or not the applicant is creditworthy but also to attract quality credit applicants who can subsequently be retained and controlled while maintaining an overall profitable portfolio.

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**CASE STUDY: CONSUMER CREDIT SCORING**

**Description**

In credit business, banks are interested in information regarding whether or not prospective consumers will pay back their credit. The aim of credit scoring is to model or predict the probability that consumers with certain characteristics are to be considered as potential risks.

The example in this case will illustrate how to build a credit scoring model using *STATISTICA* Data Miner to identify inputs or predictors that differentiate risky customers from others (based on patterns pertaining to previous customers) and then use these inputs to predict the new risky customers. This is a sample case typical for this domain.

The sample data set used in this case, CreditScoring.sta, has 1,000 cases and 20 variables or predictors pertaining to past and current customers who borrowed from a German bank (source: [http://www.stat.uni-muenchen.de/service/datenarchiv/kredit/kredit_e.html](http://www.stat.uni-muenchen.de/service/datenarchiv/kredit/kredit_e.html)) for various reasons. The data set contains various information related to the customers’ financial standing, reason to loan, employment, demographic information, etc.

For each customer, the binary outcome (dependent) variable “creditability” is available. This variable contains information about whether each customer’s credit is deemed good or bad. The data set has a distribution of 70% creditworthy (good) customers and 30% not creditworthy (bad) customers. Customers who have missed 90 days of payment can be thought of as bad risk, and the customers who have ideally missed no payment can be thought of as good risk. Other typical measures for determining good and bad customers