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Analisi del Rischio Applicata alla Frode Fiscale Utilizzando Tecniche di Data Mining

Le tecniche di data mining sono state finalizzate all'individuazione delle frodi nella richiesta dei crediti d'imposta per "investimenti in aree svantaggiate". La scelta dello strumento è stata suggerita dai brillanti risultati ottenuti in ambiti analoghi (ad es. le frodi con carte di credito). Il modello associa a ciascun soggetto un punteggio che misura la probabilità che la richiesta sottintenda una frode. La sperimentazione condotta sul campo ha fornito risultati molto soddisfacenti (percentuale di successo dell'82%). Lo strumento si configura, quindi, molto indicato per perseguire altri tipi di frode, poste in essere tramite procedure automatizzate, che coinvolgono un ampia platea di contribuenti (come le compensazioni di imposta o le richieste di rimborsi).

1. Introduction[1]

The fight against tax evasion in Italy is particularly complex also due to the fact that the economic system is characterized by a larger number of enterprises in comparison to that of other industrialized Countries. The huge presence of small businesses characterizes Italian tax evasion as a mass phenomenon that, for this reason, is very expensive to fight. As a result there is a need for instruments able to block the evasion and deal with bulk loads of data. The proposed assignment is positioned in this line of research and applies the techniques of data mining to determine the fraud risk for a specific tax performance: collectible tax credits deriving from investments made in disadvantaged areas (hereafter tax credits).

2. Adopted procedures

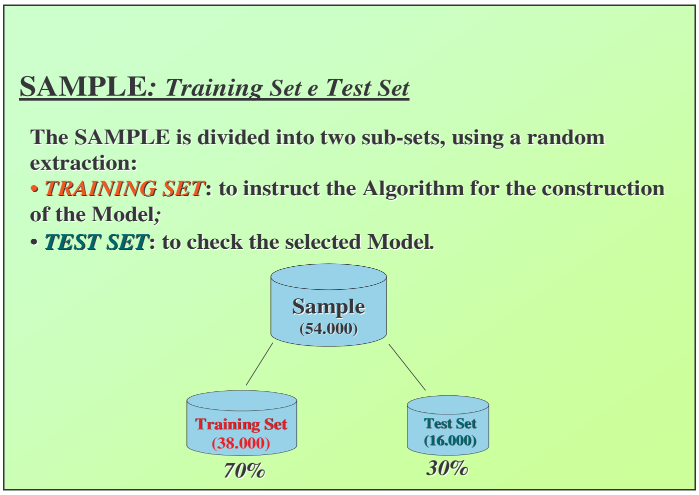
A Sample of 54.517 subjects who, having already undergone a fiscal control on tax credits, are known to be tax evaders or not, were selected from a Population of 230.000 tax payers. The variable Target was then established, defining the evader as a subject who had in fact used the undue credit and, towards whom the Internal Revenue Agency could demand a restitution. In the exploratory phase several data banks of the Internal Revenue Agency were integrated in order to obtain as much information as possible relative to the economic-fiscal behaviour of the tax payers included in the sample.

From the initial data set a random sub-sample of 38.497 units (*training set*) was extracted and used to instruct the algorithm for the construction of the model to consent the determination of the tax evader profile risk, based on the target variable (see fig. 1).

Among the possible algorithms utilizable for the construction of the model it was decided to apply the one based on the *decision tree*, since it allows the visualization of a series of decisions easily transformable into operative indications for the control activities. The recursive partitioning algorithm used is CART and ID3 (Intelligent Miner-IBM). In the next phase the model was tested on that part of the sample excluded from the training phase (*test set* including 16.019 tax payers), evaluating the effectiveness of the adaptation by using the “Confusion matrix”. Since the object of the procedure was to use the risk analysis to perform ex-post controls, the model with the highest *precision* was chosen, to minimize the costs incurred from controls on the *false positives (see fig. 2).*

([1]) A preliminary version of this paper has been presented at the conference “Rischio e Previsione”, organised by the Italian Statistical Association (SIS), Venice 6-8 June 2007.

Figure1. Decomposition of sample set in training set and test set

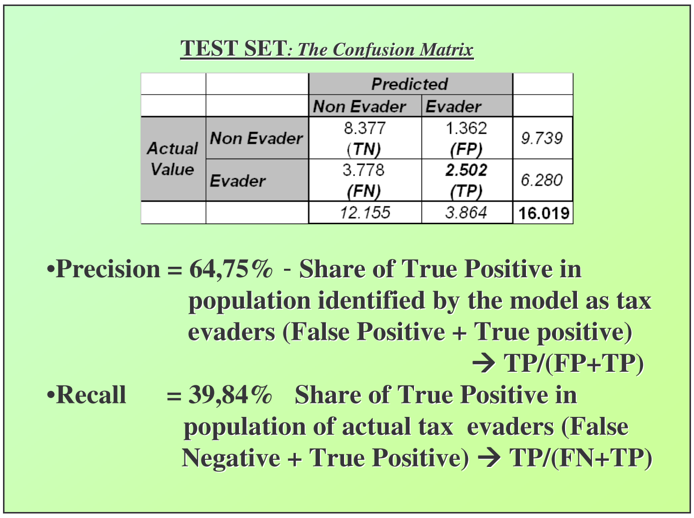


SAMPLE: *Training Set e Test Set*

The SAMPLE is divided into two sub-sets, using a random extraction:

- *TRAINING SET*: to instruct the Algorithm for the construction of the Model;
- *TEST SET*: to check the selected Model.

Figure 2. Confusion matrix obtained by the adoption of the selected model



TEST SET: *The Confusion Matrix*

		Predicted		
		Non Evader	Evader	
Actual Value	Non Evader	8.377 (TN)	1.362 (FP)	9.739
	Evader	3.778 (FN)	**2.502** (TP)	6.280
		12.155	3.864	**16.019**

•Precision = 64,75% - Share of True Positive in population identified by the model as tax evaders (False Positive + True positive) → TP/(FP+TP)

•Recall = 39,84% Share of True Positive in population of actual tax evaders (False Negative + True Positive) → TP/(FN+TP)

Finally the model was applied to the totality of the reference population (230.000 subjects).

The leaf node renders, for the rule extracted, a prediction of the fraudulent class, that is the score attributed to subjects belonging to the class taken into consideration. This prediction is derived from the relationship between the number of subjects included in the fraudulent class divided by the total of subjects present in the leaf node. The Score assumes a value included between zero and one (maximum risk). Placing the score's threshold at 0,85 in the test sample and considering the subjects above this value, it was demonstrated that the precision is equal to 0,82, a value considered acceptable; since on 100 controlled tax payers, the model tells us that 82 will be tax evaders and the error would be limited to 18 subjects.

Table 1. *Variable target distribution (non evaders = 0; evaders = 1) in the actual distribution and in the subset obtained placing the threshold at score = 0,85*

Target variable	Sample actual distribution	Sub- set with score = 0,85
0 - non evaders	59.5%	17.8%
1- evaders	39.5%	82.2%

3. Conclusion

The experiment provided extremely satisfying results, since a sector examination has produced a rate of 82% positive controls, equal to the probability estimated through the model. Furthermore, it has maximized the use of the information contained in the administrative data bases, obtaining indicators on the probability of being tax evaders solely from observing the information already available at the Internal Revenue Agency on each individual tax payer.

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