A TOPSIS Data Mining Demonstration and Application to Credit Scoring

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ABSTRACT

The technique for order preference by similarity to ideal solution (TOPSIS) is a technique that can consider any number of measures when seeking to identify solutions close to an ideal and far from a nadir solution. TOPSIS traditionally has been applied in multiple criteria decision analysis. In this article, we propose an approach to develop a TOPSIS classifier. We demonstrate its use in credit scoring, providing a way to deal with large sets of data using machine learning. Data sets often contain many potential explanatory variables, some preferably minimized, some preferably maximized. Results are favorable by a comparison with traditional data mining techniques of decision trees. Proposed models are validated using Mont Carlo simulation.

Keywords: classification; data mining; machine learning; Monte Carlo simulation; TOPSIS

INTRODUCTION

The technique for order preference by similarity to ideal solution (TOPSIS) is a classical method to solve multicriteria decision-making (MCDM) problem first developed by Hwang and Yoon (1981), subsequently discussed by many (Chu, 2002; Olson, 2004b; Peng, 2000). TOPSIS is based on the concept that alternatives should be selected that have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS), or nadir. The PIS has the best measures over all attributes, while the NIS has the worst measures over all attributes.

Multiattribute decision-making (MCDM) problem recently has received attention from artificial intelligence, machine learning, and data mining communities (Arie & Leon, 2005; Spathis, Doumpos, & Zopounidis, 2002; Zopounidis & Doumpos, 1999). Based on preference disaggregation approach estimates, a set of additive utility functions and utility profiles using linear programming techniques, Zopounidis and Doumpos (1999) present an application of the Utilities Additives Discriminantes (UTADIS) method in real-world classification problems concerning the field of financial distress. Spathis et al. (2002) proposed a multicriteria decision aid method for an innovative classification methodology in detecting firms' falsified financial statements (FFS) and in identifying the factors associated with FFS. The proposed method is believed to outperform traditional statistical techniques on a sample of 76 Greek firms.

As an MCDM technique, TOPSIS also provides a mechanism that is attractive in data mining (Olson & Wu, 2005), because it can consider a number of attributes in a systematic way without very much subjective human input. Data, whether discrete or continuous, are standardized to a range between 0 and 1. TOPSIS does include weights over the attributes that are considered. However, such weights can be obtained through regression of standardized data (where measurement scale differences are eliminated (Olson, 2004b). This allows machine learning in the sense that data can be analyzed without subjective human input. This article demonstrates the method to automatically classify credit score data into groups of high expected repayment and low expected repayment, based upon the concept of TOPSIS.

TOPSIS FOR DATA MINING

The overall approach is to begin with a set of data, which, in traditional data mining practice, is divided into training and test sets. Data may consist of continuous or binary numeric data, with the outcome variable being binary. A training data set is used to identify maximum and minimum measures for each attribute. The training set then is standardized over the range of 0 to 1, with 0 reflecting the worst measure and 1 the best measure over each attribute. Then, relative weight importance is obtained by regression over the standardized data in order to explain outcome performance in the training data set. (An intermediate third data set could be created for generation of weights, if desired.)

TOPSIS DATA MINING METHOD

The algorithm we propose consists of following steps:

Step 1: Data Standardization

In accordance with the prior presentation, training data set is standardized so that each observation j over each attribute i is between 0 and 1. Let the decision matrix X consist of m indicators over n observations. The normalized matrix transforms the X matrix. For indicator i = 1 to m, identify the minimum x_i^- and the maximum x_i^+. Then, each observation x_i^j for j = 1 to n can be normalized by the following formulas:

For measures to be maximized:

$$y_i^j = \frac{x_i^j - x_i^-}{x_i^+ - x_i^-} \tag{1}$$

For measures to be minimized:

$$y_i^j = 1 - \frac{x_i^j - x_i^-}{x_i^+ - x_i^-} \tag{2}$$

which yields values between 0 (the worst) and 1 (the best).

Step 2: Determine Ideal and Nadir Solutions

The ideal solution consists of standardized values of 1 over all attributes, while the nadir solution consists of values of 0 over all attributes.

Step 3: Calculate Weights

In decision analysis, these weights would reflect relative criterion importance (as long as scale differences are eliminated through standardization). Here, we are interested in the relative value of each attribute in explaining the outcome of each case. These m weights w_i

will be between 0 and 1 and will have a sum of 1. Because weights are continuous, we use ordinary least squares (OLS) regression over the standardized data in order to obtain $i = 1$ to m different weights from regression β_i coefficients.

$$0 \le w_i \le 1, \ \sum_{i=1}^{m} w_i = 1$$

Step 4: Calculate Distances

TOPSIS operates by identifying D_i^+ the weighted distance from the ideal, and D_i^- the weighted distance from the nadir. Different metrics, such as L_1, L_2, or L_∞, could be used (Dielman, 2005; Freimer & Yu, 1976). Least absolute value regression (L_1) has been found to be useful when it is desired to minimize the impact of outlying observations and has been shown to be effective in a variety of applications, such as real estate valuation (Caples & Hanna, 1997) and sports ratings (Bassett, 1997). The ordinary least squares metric L_2 is widely used. The Tchebychev metric (L_∞) focuses on the extreme performance among the set of explanatory variables. Each metric focuses on the different features described. Olson (2004) found L_1 and L_2 to provide similar results, both better than L_∞. The weights from Step 3 are used. Lee and Olson (2004) compared different metrics for predicting outcomes of binary games and found L_2 and L_∞ to provide similar results, both better than L_1. Thus, none of these metrics is clearly superior to the others for any specific set of data. For L_1 metric, the formula of weighted distance from the ideal is:

$$D_j^{1+} = \sum_{i=1}^{m} w_i \times (1 - y_j) \text{ for } j = 1 \text{ to } n \quad (3)$$

The weighted distance from the nadir solution is:

$$D_j^{1-} = \sum_{i=1}^{m} w_i \times (y_j) \text{ for } j = 1 \text{ to } n \quad (4)$$

The formulas for L_2 metric are very similar:

$$D_j^{2+} = \sqrt{\sum_{i=1}^{m} w_i^2 \times (1 - y_j^2)} \text{ for } j = 1 \text{ to } n \quad (5)$$

The weighted distance from the nadir solution is:

$$D_j^{2-} = \sqrt{\sum_{i=1}^{m} w_i^2 \times (y_j^2)} \text{ for } j = 1 \text{ to } n \quad (6)$$

The L_∞ metric (the Tchebycheff metric) by formula involves the infinite root of an infinite power, but this converges to emphasizing the maximum distances. The weights become irrelevant. Thus, L_∞ distance measures are:

$$D_j^{\infty-} = \text{MAX}\{y_{ij}\}; \ D_j^{\infty+} = \text{MAX}\{1 - y_{ij}\} \quad (7)$$

Step 5: Calculate Closeness Coefficient

Relative closeness considers the distances from the ideal (to be minimized) and from the nadir (to be maximized) simultaneously through the TOPSIS formula:

$$C_j = \frac{D_j^{L-}}{D_j^{L-} + D_n^{L+}} \quad (8)$$

Step 6: Determine Cutoff Limit for Classification

The training data set contained a subset of observations in each category of interest. In a binary application (e.g., segregating training observations into loans that were defaulted *Neg* and loans that were repaid *Pos*), the proportion of *Neg* observations P_{Neg} is identified. The closeness coefficient C_j has high values for cases that are close to the ideal and far from the nadir and, thus, can be sorted with low values representing the worst cases. Thus, the rank of the largest sorted observation in the *Neg* subset J_{Neg} would be $P_{Neg} \times (Neg + Pos)$. The cutoff limit *CLim* can be identified as a value greater than that of

Table 1. Independent variables for Canadian banking data set

Variable		Training Set Minimum Value	Training Set Maximum Value	Goal
Total Assets	TA	332	421,029	Maximize
Capital Assets	CA	107	269,188	Maximize
Interest Expense	IE	0	70,938	Minimize
Stability of Earnings	INSTAB	34.781	74,672.86	Maximize
Working Capital	WC	-403,664	169,523	Maximize
Total Current Liabilities	CL	33	578,857	Minimize
Total Liabilities	TL	33	584,698	Minimize
Retained Earnings	RE	-486,027	225,719	Maximize
Shareholder Equity	SE	-430,935	298,903	Maximize
Net Income	NI	-238,326	97,736	Maximize
Earnings Before Tax and Depr.	EBITDA	-132,388	158,401	Maximize
Cash Flow from Operations	CF	-41,387	95,427	Maximize

ranked observation J_{Neg} but less than that of the next largest ranked observation.

Step 7: Apply Formula

For new cases with unknown outcomes, the relative closeness coefficient C_j can be calculated by formula (7) and compared with the cutoff limit obtained in Step 6. The only data feature that needs to be considered is that it is possible for test data to contain observations outside the range of data used to determine training parameters.

IF $y_{ij} < 0$ THEN $y_{ij} = 0$
IF $y_{ij} > 1$ THEN $y_{ij} = 1$

This retains the standardized features of test data. The model application then is obtained by applying the rules to test data:

IF $C_j < CLim$ THEN classification is Negative
IF $C_j > CLim$ THEN classification is Positive

Model fit is tested by traditional data mining coincidence matrices.

EXPERIMENT DATA SET

A company's financial performance can be represented by various ratios taken from financial statements (Barnes, 1987; Deng, Yeh, & Willis, 2000). Such ratios provide useful information in order to describe credit conditions from various perspectives, such as financial conditions and credit status. The diagnostic process involves multiple criteria. We present a real set of loan cases from Canadian banking. The data reflect operations in 1995 and 1996. There are 177 observations for 1995 (17 defaulting, 160 good) and 126 (11 defaulting, 115 good) for 1996. While the data set is unbalanced (banks would hope that it was), it is typical. Models for decision trees can be susceptible to degeneration, as they often classify all observations in the good category (Olson, 2004). This did not prove to be a problem with this data set, but Laurikkala (2002) and Bull (2005) provide procedures to deal with such problems of unbalanced data, if they detrimentally affect data mining models. The data set consisted of the outcome variable (categorical: default, good) and 12 continuous numeric independent variables, as given in Table 1.

This data set demonstrates many features encountered with real data. Most variables are to be maximized, but here, three of the 12 variables would have the minimum as preferable. There are negative values associated with the data set, as well.

TOPSIS MODEL OVER TRAINING DATA

Step 1: Data Standardization

The data set was standardized using formulas (1) and (2).

Step 2: Determine Ideal and Nadir Solutions

The ideal solution here is a vector of standardized scores of 1:

{1 1 1 1 1 1 1 1 1 1 1 1}

reflecting the best performance identified in the training set for each variable. The nadir solution is conversely:

{0 0 0 0 0 0 0 0 0 0 0 0}

All n observations would have a standardized score vector consisting of m (here, $m = 12$) values between 0 and 1.

Step 3: Calculate Weights

Weights were obtained by regressing over the standardized data with the outcome of 0 for default and 1 for no default. Table 2 shows the results of that regression (using ordinary least squares).

This model had an R-Square value of 0.287 (adjusted R-Square of 0.235), which was relatively weak. Correlation analysis indicated a great deal of multicollinearity (demonstrated by the many insignificant beta coefficients in Table 2), so a trimmed model using the three uncorrelated variables of NI, EBITDA, and CF was run. This trimmed model had an R-Square of 0.245 (adjusted R-Square of 0.232), but the predictive capability of this model was much weaker than the full model. Multicollinearity would be a problem with respect to variable β coefficient significance, but since our purpose is prediction of the overall model rather than interpretation of the contribution of each independent variable, this is not a problem in this application. Therefore, the full regression model was used. Weights obtained in Step 3, therefore, are given in the last column of Table 2. However, these weights should not be interpreted as accurate reflections of variable prediction importance due to the model's multicollinearity, which makes these weights unstable, given overlapping information content.

Table 2. Standardized data regression

Variable	Regression Coefficient β_i	P-Value	Absolute Value of β_i	Proportional Weight
TA	-1.4205	0.926	1.4205	0.103
CA	0.5263	1.000	0.5263	0.038
IE	-1.7013	0.043	1.7013	0.123
INSTAB	-0.3245	0.453	0.3245	0.023
WC	-0.1028	1.000	0.1028	0.007
CL	0.3010	1.000	0.3010	0.022
TL	-0.6058	0.977	0.6058	0.044
RE	0.3551	0.477	0.3551	0.026
SE	2.1597	0.935	2.1597	0.156
NI	3.3446	0.051	3.3446	0.242
EBITDA	-2.2372	0.084	2.2372	0.162
CF	0.7510	0.056	0.7510	0.054
Totals			**13.8298**	**1.000**

Step 4: Calculate Distances

Three metrics were used for TOPSIS models in this study. For L_1 model, the values for D_i^{1+} were obtained by generating by formula (3) for each observation over each variable in the training set, and D_i^{1-} obtained by formula (4). Formulas (5) and (6) were used for L_2 model, and formulas given in (7) for L_∞ model.

Step 5: Calculate Closeness Coefficient

Formula (8) was applied to the distances obtained in Step 4 for the training set.

Step 6: Determine Cutoff Limit for Classification

The 177 closeness coefficient values then were sorted, obtaining a 17th ranked closeness coefficient and an 18th ranked closeness coefficient. For L_1 model, these were 0.56197 and 0.561651. Thus, an L_1 cutoff limit of 0.5615 was obtained for application on test set and for classification of future values. For L_2 model, the corresponding numbers were 0.410995 and 0.412294, yielding a cutoff limit of 0.411. For L_∞ model, these numbers were 0.624159 and 0.624179, and a cutoff limit of 0.62416 was used.

Step 7: Application of Model

The last step is to apply models to test data. Results are given in Section 5.

MODEL COMPARISONS

The original raw data were used with two commercial data mining software tools (PolyAnalyst and See5) for decision tree models. PolyAnalyst decision tree model used only two variables: NI and WC. The decision tree is given in Figure 1.

This model had a 0.865 correct classification rate over test set of 126 observations, as shown in Table 3.

The errors in this model were a bit more proportional in the bad case of assigning actual default cases to the predicted on-time payment category. However, cost vectors were not used, so there was no reason to expect the model to reflect this. See5 software yielded the following decision tree, using four independent variables.

Table 4 shows the results for the decision tree model obtained from See5 software, which had a correct classification rate of 0.817, just a little worse than the PolyAnalyst model (although this is for specific data and in no way is generalizable).

Figure 1. PolyAnalyst decision tree

```
IF NI < 1250
        AND IF WC < 607 THEN 0 (Neg)
        ELSE IF WC >= 607 THEN 1 (Pos)
ELSE IF NI >= 1250 THEN 1 (Pos)
```

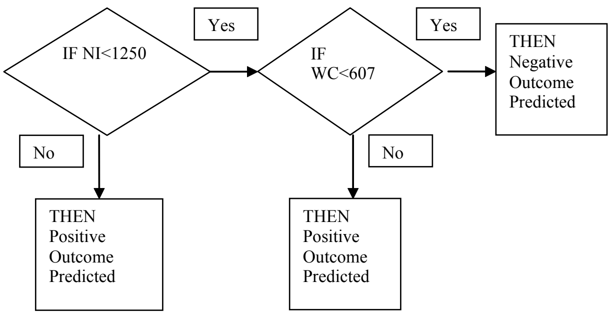
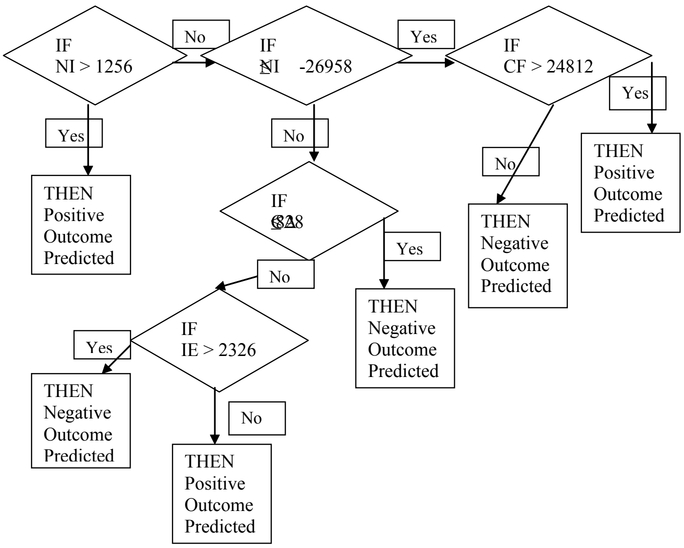


Table 3. Coincidence matrix—PolyAnalyst decision tree

	Model 0 (Neg)	**Model 1 (Pos)**	
Actual 0 (Neg)	9	**2**	11
Actual 1 (Pos)	**6**	109	115
	15	111	126

Figure 2. See5 decision tree

```
IF NI > 1256 THEN 1 (Pos)
            ELSE IF NI <= -26958
            AND IF CF > 24812 THEN 1 (Pos)
                        ELSE IF CF <= 24812 THEN 0 (Neg)
            IF NI > -26958 AND CA <= 828 THEN 0 (Neg)
                        ELSE IF CA > 828 AND IE <= 2326 THEN 1 (Pos)
                                    ELSE IF IE > 2326 THEN 0 (Neg)
```



Finally, TOPSIS models were run. Results for L_1 model are given in Table 5, with a correct classification rate of 0.944.

The results for L_2 model are given in Table 6, with a correct classification rate of 0.921.

The results for L_∞ model are given in Table 7, with a correct classification rate of 0.844. Here, all three metrics yield similar results (for this data, superior to decision tree models, but that is not a generalizable conclusion).

The results for the different models are given in Table 8.

These models were applied to one data set, demonstrating how TOPSIS principals can be applied to data mining classification. In this one small (but real) data set for a common data mining application, TOPSIS models gave a better fit to test data than did two well-respected decision tree software models. This does not imply that TOPSIS models are better, but it provides another tool for classification. TOPSIS models are easy to apply in spreadsheets with however much data can be fit into a spreadsheet.

Table 4. Coincidence matrix (see5 decision tree)

	Model 0 (Neg)	**Model 1 (Pos)**	
Actual 0 (Neg)	8	**3**	11
Actual 1 (Pos)	**13**	102	115
	21	105	126

Table 5. Coincidence matrix—TOPSIS L_1 model

	Model 0 (Neg)	**Model 1 (Pos)**	
Actual 0 (Neg)	6	**5**	11
Actual 1 (Pos)	**2**	113	115
	8	118	126

Table 6. Coincidence matrix—TOPSIS L_2 model

	Model 0 (Neg)	**Model 1 (Pos)**	
Actual 0 (Neg)	6	**5**	11
Actual 1 (Pos)	**5**	110	115
	11	115	126

Any number of independent variables could be used, limited only by database constraints.

SIMULATION OF MODEL RESULTS

Monte Carlo simulation provides a good tool to test the effect of input uncertainty over output result (Olson & Wu, 2006). Simulation was applied in order to examine the sensitivity of five models to perturbations in test data. Each test data variable value was adjusted by adding an adjustment equal to:

$$\text{Perturbation} \times \text{Uniform random number} \times \text{Standard normal variate}$$

The perturbations used were 0.25, 0.5, 1, and 2. These values reflect increasing noise in the data. The adjustments are standard normal variates with mean 0 and standard deviation found in the training data set for that variable.

Simulation results are shown in Table 9.

The first decision tree model was quite robust and, in fact, retained its predictive power the most of all five models as perturbations were increased. The second decision tree model included more variables and a more complex decision tree. However, it not only was less accurate without perturbation, but it also degenerated much faster than the simple 2 variable decision tree. While this is not claimed as generalizable, it is possible that simpler trees could be more robust. (As a counterargument, models using more variables may have less reliance on specific variables subjected to noise, so this issue merits further exploration.)

The L_1 and L_2 TOPSIS metrics had less degeneration than the four-variable decision tree but a little more than the two-variable decision tree. The L_1 TOPSIS model was less affected by perturbations than was the L_2 model, which, in turn, was quite a bit less affected than was the L_∞ model. This is to be expected, as the L_1 model is less affected by outliers, which can be generated by noise. The L_∞ model focuses

Table 7. Coincidence matrix—TOPSIS L_∞ model

	Model 0 (Neg)	Model 1 (Pos)	
Actual 0 (Neg)	6	**5**	11
Actual 1 (Pos)	**2**	113	115
	8	118	126

Table 8. Comparison of model results

Model	Actual 0 Model 1	Actual 1 Model 0	Proportion Correct
PolyAnalyst Decision Tree	2	6	0.937
See5 Decision Tree	3	13	0.873
TOPSIS L_1	5	2	0.944
TOPSIS L_2	5	5	0.921
TOPSIS L_∞	5	2	0.944

Table 9. Simulation results

Perturbation	PADT Min	PADT Max	C5 Min	C5 Max	L1 Min	L1 Max	L2 Min	L2 Max	L∞ Min	L∞ Max
0	0.9365	0.9365	0.8730	0.8730	0.9444	0.9444	0.9206	0.9206	0.9444	0.9444
0.25	0.7381	0.9365	0.6746	0.8651	0.7619	0.9286	0.7619	0.9127	0.6825	0.8889
0.50	0.7063	0.9444	0.5952	0.8413	0.7143	0.8968	0.6190	0.8730	0.6349	0.8492
1.0	0.6905	0.8968	0.5317	0.7937	0.6349	0.8492	0.5873	0.8333	0.4683	0.7460
2.0	0.6587	0.8968	0.5238	0.7857	0.5714	0.8175	0.5476	0.7937	0.3810	0.6508

on the worst case, which is a reason for it to be adversely impacted by noise in data.

CONCLUSION

TOPSIS is attractive in that it follows automatic machine learning principles. TOPSIS originally was presented in the context of multiple criteria decision making, where the relative importance decision maker preference was a factor and subjective weights were input. In data mining applications presented here, the weights are obtained from data, removing the subjective element. Weights here reflect how much each independent variable contributes to the best ordinary least squares fit to data. Data standardization removes differences in scale across independent variables. Thus, TOPSIS models provide a straightforward way in which to classify data with any number of independent variables and observations.

The classical methods for classification and decision trees are valuable tools. Decision trees have a useful feature that can provide an easy way to interpret rules, as shown in step 5 of our method. In the spirit of data mining, TOPSIS models presented in this article can provide an additional tool for comparative analysis of data.

We presented three metrics in this article. The L_2 metric traditionally is used, although L_1 and L_∞ metrics are just as valid. The L_1 metric usually is considered less susceptible to the influence of outlier data, as squaring the distance from the measure of central tendency in

L_2 metric has a greater impact. In Tchebycheff L_∞ metric, the greatest difference determines the outcome, which is attractive in some contexts. If outliers are not intended to have a greater influence, L_1 metric might be preferred. If all variables are to be considered to the greatest degree, L_∞ metric is attractive. Here, however, we confirm prior results cited and find that L_2 metric seems to perform very well.

Simulation was used to demonstrate relative model performance under different levels of noise. While simulation of data mining models involves extra computations, it can provide insight into how robust those models are expected to be.

Nevertheless, future research about TOPSIS data mining is suggested. The possible direction includes developing new techniques that can be compared and contrasted with the linear regression approach used in this article to derive the weights for independent decision variables.

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