Use Data Mining Techniques to Assist Institutions in Achieving Enrollment Goals: A Case Study

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1

Data Mining: Concepts

- SAS: "the process of sampling, exploring, modifying, modeling, and assessing (SEMMA) large amounts of data to uncover previously unknown patterns, which can be utilized as a business advantage." (Applying Data Mining, 2005, p. 1-3)
- Microsoft: "Data mining is the process of discovering actionable information from large sets of data. Data mining uses mathematical analysis to derive patterns and trends that exist in data." (<u>http://technet.microsoft.com/en-us/library/ms174949.aspx</u>)
- Berry and Linoff: "Data mining is the exploration and analysis of large quantities of data in order to discover meaningful patterns and rules. ...the goal of data mining is to allow a corporation to improve its marketing, sales, and customers." (Data Mining Techniques, p.7).

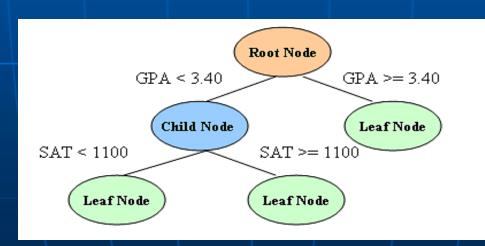
Data Mining: What Can We Do with It?

- Classification: discrete outcomes: yes or no
- Estimation: continuous values outcomes
- Prediction: the same as classification or estimation, but classifying according to some predicted future behavior or estimated future value
- Association Rules: determine which things go together
- Clustering: segment a heterogeneous population into a number of more homogeneous subgroups or clusters
- Description and Profiling: simply describe what is going on in a complicated database

Data Mining: Techniques—Decision Tree

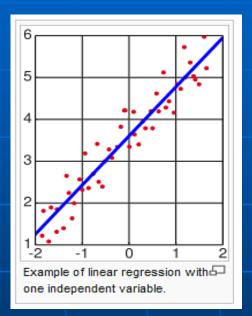
Decision Tree

- Divide up a large collection of records into smaller sets of records using decision rules
- Process: Record \rightarrow Root Node \rightarrow Child Node \rightarrow Leaf Node
- The PATH is an expression of the rules used to classify the records.
 - 3 paths in this tree
 - GAP>=3.40
 - GPA<2.40 \rightarrow SAT>=1100
 - GPA<3.40 \rightarrow SAT < 1100

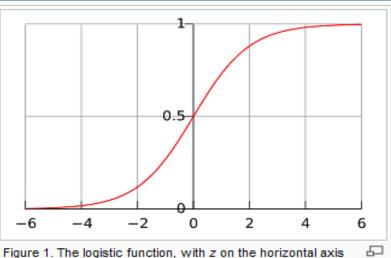


Data Mining: Techniques—Regression (Logistic Regression)

Regression



Logistic Regression

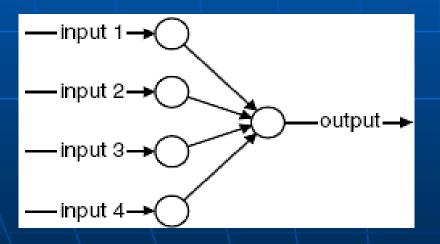


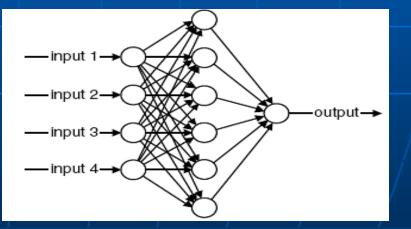
and f(z) on the vertical axis.

Data Mining: Techniques—Neural Network

Neural Network

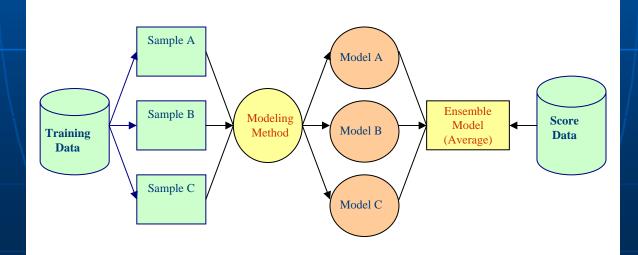
- Similar property of biological neurons
- Interconnected artificial neurons
- Inputs \rightarrow Hidden Layer \rightarrow Output(s)
- Weights
 - Inputs and Hidden Layer
 - Hidden Layer and Output





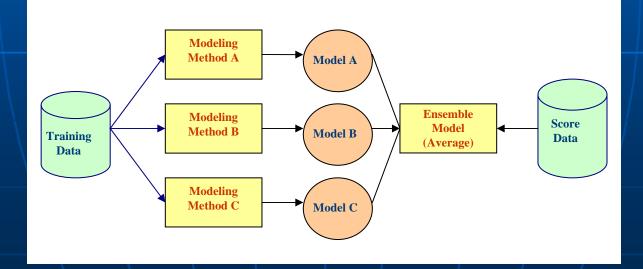
Data Mining: Techniques—Ensemble

- Ensemble: Averaging the posterior probabilities for class targets or the predicted values for interval targets from multiple models
- Methods:
 - Different models from the same modeling method based on separate samples of training data set



Data Mining: Techniques—Ensemble

- Ensemble: Averaging the posterior probabilities for class targets or the predicted values for interval targets from multiple models
- Methods:
 - Different models from the same modeling method based on three separate samples of training data set
 - Different models from the different modeling methods based on the same training data set

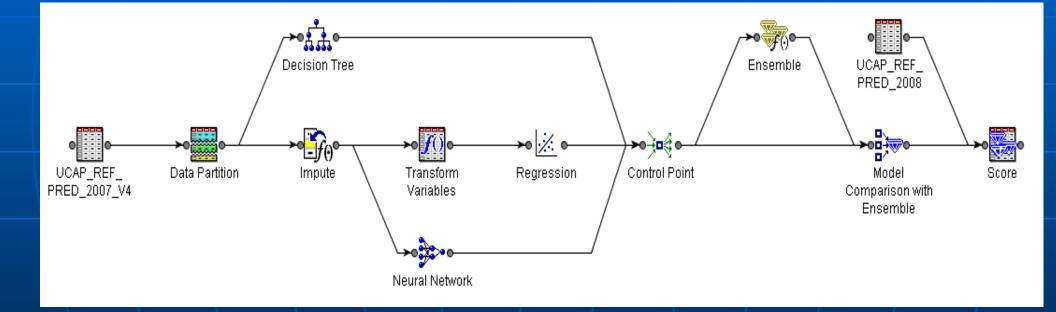


Data Mining: Applications in Institutional Research

- College admissions yield (Chang, 2006)
- **Retention** (Herzop, 2006; Sujitparapitaya, 2006)
- **Time to degree** (Eykamp, 2006; Herzop, 2006)
- **Enrollment management** (Aksenova, Zhang, & Lu, 2006)
- Course offerings (Luan, 2006; Dai, Yeh, & Lu, 2007)
- Student performance (Dede & Clarke, 2007; Heathcote & Dawson, 2005; Minaei-Bidgoli, 2004; Ogor, 2007)
- **Graduation rate** (Baily, 2006)
- Student experience survey study (Yu, et. al, 2007)

A Case Study Using SAS Enterprise Miner

Assist Institutions in Achieving Enrollment Goals



A Case Study Using SAS Enterprise Miner—Background

- Paths to Eligibility for CA Residents at UC
 - Eligibility in the Statewide Context
 - Eligibility in the Local Context (ELC)
 - Eligibility by Examination Alone
- Admissions:
 - UC guarantees to admit all CA eligible applicants, but does not guarantee to admit everyone in terms of the campus or the program he/she applied to.

A Case Study Using SAS Enterprise Miner—Background Referral Pool:

- Eligible, not admitted
- To the <u>referral pool</u>
- Two UC campuses: <u>Riverside</u> and <u>Merced</u>
- Don't know until April, too late, so the yield rate is low
- Early Referral Pool:
 - A letter to those who may be in the referral pool
 - Admit those who would like to consider these two campuses
- Question: Who do we send a letter to?

A Case Study Using SAS Enterprise Miner—Purpose

- Predict UC applicants who are qualified to UC admissions systemwide, but not admitted to the campus they applied to
- Two campuses use the information to make Early Referral Pool admissions offers and try to enroll more students.

A Case Study Using SAS Enterprise Miner—Data Description

- UC Freshman Application Data
 - Data Sets:
 - Fall 2007 data, training data
 - Fall 2008 data, target data
 - Observations (Eligible Applicants):
 - Fall 2007: 45,393
 - Fall 2008: 48,356
 - Elements
 - Student demographic and academic information
 - Family information
 - Application information (campuses, major, etc.)
- CDE School Performance Data
 - Academic Performance Index (API)

A Case Study Using SAS Enterprise Miner—Variables

Variable	Data Type	Description				
Referral Pool	Dichotomous	Dependent variable: 1=in referral pool, 0=not in referral pool				
Ethnicity	Categorical	7 categories				
First Language	Categorical	3 categories: English Only, English and Another Language, and Another Language				
Campus(es) Applied to	Categorical	7 variables, one for each campus: e.g. CAMP_BK: 1=applied to UC Berkeley, 0=not applied to UC Berkeley				
Parent's Educational Level	Categorical	5 Categories: HS or Less, 2 Year College, 4 Year College and Post Ed. Study, Missing				
Family Income	Continuous					
Home Location	Categorical	5 Categories: San Francisco Bay Areas, CA North, LA County, CA South, and Other				
Discipline	Categorical	7 Variables, one for each campus: 5 categories for each variable: Engineering, Science, Social Science, Humanities, Others.				
Outreach Programs	Dichotomous	Participated at least one or not participated in any one.				
API Ranking	Categorical	1 to 10 for public schools, missing for private schools				
High School GPA	Continuous	Weighted, Capped GPA				
UC Score (SAT or ACT)	Continuous	Highest of converted SAT or ACT score, including 2 highest SAT subject tests 15				

A Case Study Using SAS Enterprise Miner—Missing Value Imputation

- Categorical Variable: not necessary, "MISSING" is a category.
- Continuous Variable:
 - Discard vs. Impute
 - For data accuracy, simply discard, but reduce data drastically
 - Scoring problem: records with missing values will not be scored
 - Decision tree modeling: not necessary
 - Logistic regression and neural network modeling: ignore all records with missing values
 - Compare models: on the same set of observations
 - SAS Methods: 11— mean, median, mid-range, tree, etc.
 - Method for This Project: median, tree, mean, etc. were used, but the best method is mean

A Case Study Using SAS Enterprise Miner—Data Transformation

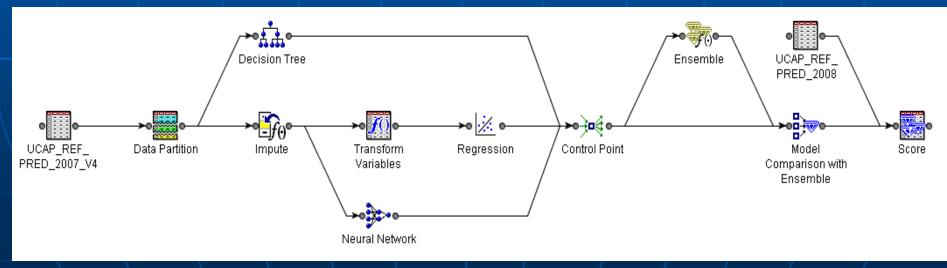
- **Transformation:** highly skewed distribution, a great deal of influence
- Decision tree and neural network modeling: Flexible
- Logistic regression modeling: Transformation may yield a better fitting model



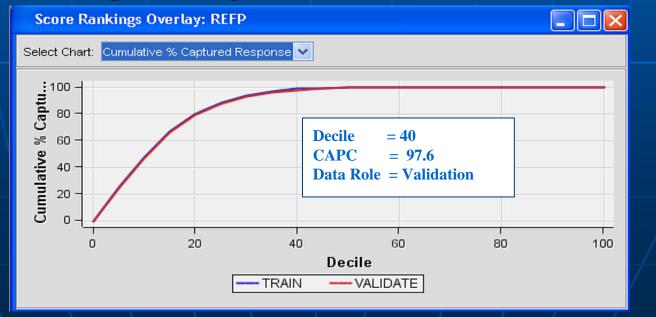
A Case Study Using SAS Enterprise Miner—Modeling Process

Data Partition:

- **Training Data Set:** Preliminary model fitting
- Validation Data Set: Monitoring and tuning the model to improve its generalization
- Test Data Set: Estimate of Generalization
- Data Set Percentage: User decides, but each observation is allowed to use only once, 40%, 30%, and 30%.
- Four Models: Decision Tree, Logistics Regression, Neural Network, and Ensemble



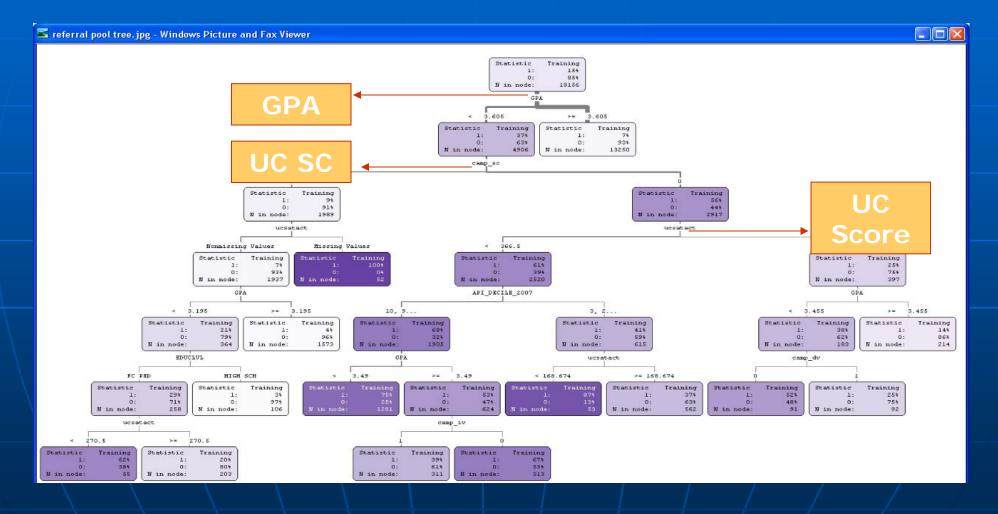
- Score Rankings Overlay
 - Lift
 - Cumulative Lift
 - Gain
 - % Response
 - Cumulative % Response
 - % Captured Response
 - Cumulative % Captured Responses



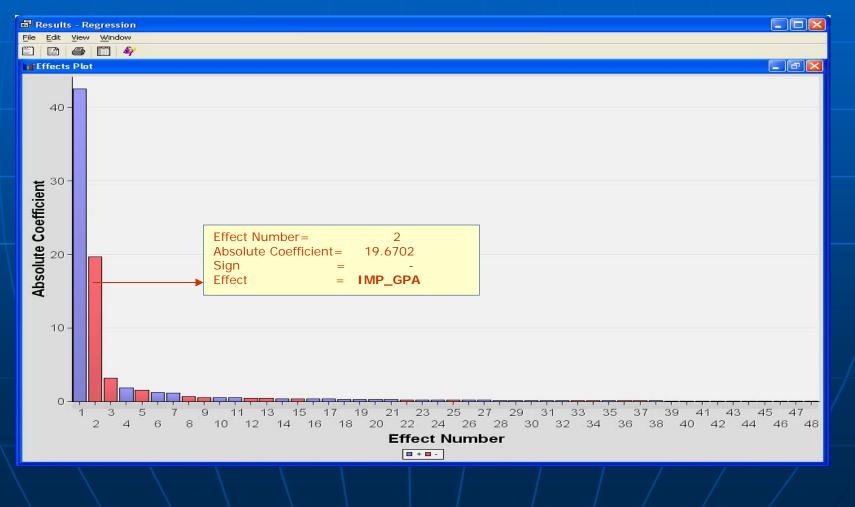
Fit Statistics

Fit Statistics						
TARGET	Fit statistics	Statistics Label	Train	Validation	Test	
REFP	_AIC_	Akaike's Information Criterion	8388.369			
REFP	_ASE_	Average Squared Error	0.071947	0.073726	0.073328	
REFP	_AVERR_	Average Error Function	0.228364	0.235384	0.235675	
REFP	_DFE_	Degrees of Freedom for Error	18108			
REFP	_DFM_	Model Degrees of Freedom	48			
REFP	_DFT_	Total Degrees of Freedom	18156			
REFP	_DIV_	Divisor for ASE	36312	27234	27240	
REFP	_ERR_	Error Function	8292.369	6410.444	6419.8	
REFP	_FPE_	Final Prediction Error	0.072329			
REFP	_MAX_	Maximum Absolute Error	0.990743	0.999043	0.997095	
REFP	_MSE_	Mean Square Error	0.072138	0.073726	0.073328	
REFP	_NOBS_	Sum of Frequencies	18156	13617	13620	
REFP	_N/V_	Number of Estimate Weights	48			
REFP	_RASE_	Root Average Sum of Squares	0.26823	0.271526	0.270791	
REFP	_RFPE_	Root Final Prediction Error	0.26894			
REFP	_RMSE_	Root Mean Squared Error	0.268585	0.271526	0.270791	
REFP	_SBC_	Schwarz's Bayesian Criterion	8763.093			
REFP	_SSE_	Sum of Squared Errors	2612.545	2007.863	1997.446	
REFP	_SUMVV_	Sum of Case Weights Times F	36312	27234	27240	
REFP	_MISC_	Misclassification Rate	0.103602	0.104502	0.105874	

Importance of a variable in modeling: Tree Map

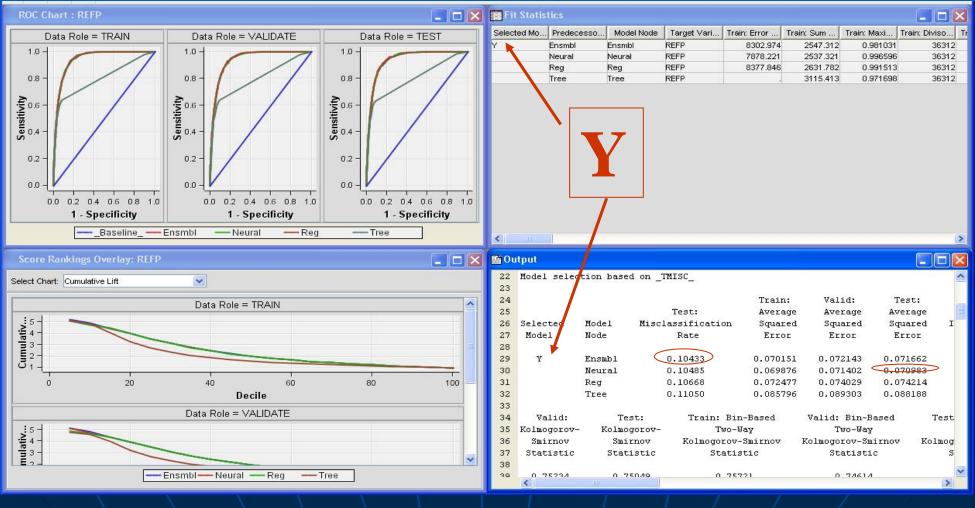


- **Tree:** The closer a variable is to the <u>root node</u>, the more prominent in the model.
- Regression Effects Plot: Displays a ranked plot of the effect scores most prominent in the model



A Case Study Using SAS Enterprise Miner—Model Comparison

- Receiver Operating Characteristics (ROC) Chart: Measure of the predictive accuracy of a model.
- Fit Statistics, Score Rankings Overlay, Output



A Case Study Using SAS Enterprise Miner—Scoring and Deployment

Scoring: Process to apply the model to new cases

- Generate SAS Code
- Cleaning target data
- Calculate probability
- Deployment:
 - A list of students with a probability equal to or above 40% to two campuses
 - Campuses sent a letter to selected students
 - Campus made offers to those students who responded, allowed campuses to review their applications (Early Referral Pool)

A Case Study Using SAS Enterprise Miner—Results

- Results: Comparison with the actual referral pool
 - Accuracy
 - In terms of the number, accuracy rate: 93%
 - In terms of individual students,

Predicted Probability	Predicted Referral Pool	Actual Referral Pool	Cumulative Accuracy Rate	Predicted Referral Pool as Cumulative % of Total Population	Actual Referral Pool as Cumulative % of the Entire Referral Pool
90 - 100%	65	52	80.0%	0.1%	0.6%
80 - 89%	353	275	77.9%	0.7%	3.3%
70 - 79%	2,732	2,018	73.9%	5.6%	23.9%
60 - 69%	4,986	3,555	71.3%	10.3%	42.0%
50 - 59%	6,659	4,597	69.0%	13.8%	54.3%
40 - 49%	8,209	5,518	67.2%	17.0%	65.2%

A Case Study Using SAS Enterprise Miner—Results

- **Results:** Comparison with the actual referral pool
 - Accuracy
 - In terms of the number, accuracy rate: 93%
 - In terms of individual students,
 - Yield

	2005	2006	2007	2008		
				Total	Early Referral Pool	Traditional Referral Pool ²
Actual Referral Pool	6,170	6,090	6,923	9,300	1,099	8,201
SIRs ¹ from Actual Referral Pool	392	398	465	769	241	528
Referral Pool Yield Rate	6.4%	6.5%	6.7%	8.3%	21.9%	6.4%
Total SIRs from All Admits	3,691	4,006	4,412	5,770		
Referral Pool SIRs as % of Total SIRs	10.6%	9.9%	10.5%	13.1%		

Data Mining Workshop Information

Summer Program for Educators Teaching Data Mining

- **Track 1**: Basic SAS programming; **Track 2**: SAS Enterprise Miner
- Location: CSU Long Beach, the SAS Campus in Cary, NC
- **Time**: Early August
- Registration Fee: No
- **Text Books:** Free
- Breakfasts and Lunches: Every day and free
- Invited people only
- Invitation letter is sent out early February
- Contact the SAS Institute in January
- Contact person: Susan Walsh, susan.walsh@sas.com