Artificial Neural Network Analysis to Observe the Credit Rating on Municipal Bonds

DESI ARISANDI
The State University of New Jersey

Abstract
In addition to providing information for the purpose of transparency and accountability, government financial and budgetary reports also supply information regarding financial performance. This information undoubtedly influences many public investment decisions including bond issuance and credit worthiness. This study is applying Artificial Neural Networks to evaluate the municipal bond credit rating. The model is incorporating budgetary information, financial information, demographic information, and bond characteristics. The main contribution of this study is to develop a model that explain the variables or factors that influence the municipal bonds credit rating. This information will beneficially for the potential issuers and investors and assists their decisions making. It is also appropriate information for the municipal bond issuer in so that they can focus more on the most crucial factors in order to maintain or improve their credit score. In summary this study will provide better understanding regarding practice and implementation of municipal bond credit ratings.

Keywords: *Artificial Neural Networks, Budget, Credit Rating, Governmental Accounting and Municipal Bonds*

1. Introduction

With the primary objective of seeking higher returns and safe investments, investors can focus their investment activities not only on the corporate investment products but also on the debt market of states, cities, and government-related entities. Many municipal bonds are considered nearly as safe as treasury investment because they are backed by the public tax revenue. Based on the latest data in 2014, municipal bonds provide return 8.32% on the average, which is higher than corporate debt (6.68%) and Dow Jones Industrial average (6.86%) (Kuriloff, 2014).

In the municipal bonds transaction, one of the primary sources of information for the investors is the credit rating agency. These agencies provide their assessments of local governments' creditworthiness through the issuance of credit ratings. In presenting their assessment through credit ratings, credit rating agencies have never clearly revealed either the variables or weight to assign on each of variables on their models, for example general description regarding debt repayment capability is described widely without specification on which borrower's characteristic that matter for measuring the ability to make repayment (Ammarz et al., 2001). These credit rating agency's policies that seem to adopt black box approach received criticism in the mid-70s, especially in the area on New York due to overrating bonds that contribute to the fiscal crisis problems. Despite the vague determination factor of credit rating, the published credit rating is found to be influencing the municipal borrowing costs or investor yield (Rubinfeld, 1973).

Various studies have shown that Artificial Intelligence (AI) methods provide better performance than traditional statistical methods. One of the methods that includes in the AI category is Artificial Neural Networks (ANN). This study decides to use ANN method instead of more conventional statistical method such as regression because from the prior finance studies showed that regression analysis application is not suitable for the research that related to the bond rating. Bond rating is an ordinal rather than an interval variables, hence the difficulty to use regular regression for analysis (Wallace, 1981).

Under general classification, ANN method can be divided into two categories (Beckmw, 2013). First is unsupervised learning which is can be used for pattern recognition. Unsupervised learning can be incorporated as the method for the detecting the compliance pattern of local government entities toward standards/regulations or general/common practice. The second category of neural network is a supervised learning. This type of neural network is generally used for prediction. I will implement supervised learning of neural network method for predicting the change of local governments' bonds (hereafter referred to as municipal bonds) credit rating change based on financial and non-financial information. The study is not purposely to reproduce the credit ratings from the major agency such as Moody, S&P or Fitch but for determine the factors that influence the rating.

The main contribution of this study is to develop a model that explain the variables or factors that influence the municipal bonds credit rating. This information will beneficially for the potential issuers and investors and assists their decisions making. It is also appropriate information for the municipal bond issuer in so that they can focus more on the most crucial factors in order to maintain or improve their credit score.

2. Theoretical Framework

The process of issuance of muni bonds is started with the announcement from the local governments. The process is followed by the bids from underwriters (primary market). The bids are handle mostly by appointed banks or underwriter companies. The selected winner is based on the lowest net interest cost for the local government entity. After the underwriter has been selected, the offer toward public is begin.

Similar to corporate bonds, municipal bonds are a type of loan that require the issuer to paid back at a specified time (maturity date) and pays a specified rate of interest (coupon rate). The maturity period of municipal bonds is usually from 1 to 30 years with some cases up to 100 years. The issuance of bonds can be in the form of a serial, which are bond issues that have different period of maturity date. This method provides the issuer to spread out the repayment of principal.

Beside financial statements, credit rating issue by credit rating agency is also an indicator of financial performance. And as one of the primary source of information, bond rating is indicated driving markets market decision in investment (Copeland & Ingram, 1982). Bond rating may directly influence the marketability of bonds and also ultimately to measure the default or risk level of investments (Ammarz, Duncombe, Hou, Jump, & Wright, 2001). However, the information that provided by the credit rating agency is not comprehensive enough to determine which factors that are observed as the leading cause of the change in municipal credit rating (Ammarz, Duncombe, Hou, Jump, & Wright, 2001). Moreover, the empirical verification by the credit rating agency is not only include financial or accounting attributes, but also non-financial data, such as demographic or future resource probability (Hastie, 1972).

There are some opinions that critic issuer-paid rating agencies, since they are paid by the companies that they are rated. It seems that there is a potential conflict of interest that present when credit rating agency issue credit rating or changes their ratings (Milidonis , 2013). In contrast to these opinions, some experts is belief that despite commercial relationship that occurred between credit rating agencies and issuers, credit rating agencies are maintaining their reputation as its most valuable assets and not willing to risk their reputation in peril. Credit rating is also affect city or state management, for example in the late 1960s, New York City's controller claimed that the city's credit rating cause additional interest cost (Liu & Thakor, 1984).

7. Focus on the government local entity credit rating, starting on November 2011, Municipal Securities Rulemaking Board (MSRB) provides publicly display for municipal credit rating through Electronic Municipal Market Access (EMMA). EMMA provides information regarding the current rating and the likelihood that there will be a rating change. However, if user need historical data regarding the prior rating to conduct time series analysis, EMMA website will not able to provide this information. There are three main rating agencies that cover for municipal credit ratings (Table and Appendix

Table 1). These rating agencies are Standard & Poor's, Fitch Ratings, and Moody's Investors Service, Inc. The following section will show the comparison summary between there major rating agencies.

Moody's gives Aaa rating for the issuers that demonstrate the best creditworthiness relative to other municipal or tax-exempt issuers or issues. The second best rating is Aa, and followed by A and Baa. Bonds within the category Aa, A, or Baa are also assigned into sub categories which are 1, 2, or 3. The smaller number that shows as the sub categories the strongest creditworthiness of this issuer.

Similar with Moody's, S&P credit rating agency assigns their rating based on the credit's worthiness, which is includes the possibility of credit quality adverse change (S&P, 2014). Credit rating issued by S&P can be either long-term or short-term. Municipal bonds usually fall into the latter categories since the maturity period is more than one year.

The ratings from Fitch can be divided into two parts: investment grade and speculative grade. Investment grade is a category for low to moderate credit risk investment. Similar with S&P's rating, this type of rating is described starting from AAA to BBB. Speculative grade category indicates relatively high credit risk or even has already claimed for financial default. Some bonds that are not rated by Fitch are denoted to NR or Not Rated.

The Government Accounting Standards Board (GASB) provides guidelines for the state and local governments in producing information for the users. This information can be utilized to measure the default or credit risk indications (Pridgen & Wilder, 2013). Supporting the need of information, agency theory hypothesizes that one of the controlling and monitoring methods for organization is accounting information (Wallace, 1981). Due to the investor's return is relying on the coupon rate and the maturity payment, the information that capable to provide the probability that the debt service will be fulfilled until the end of schedule is very important for the investors (Hastie, 1972).

From Fitch official website (Staffa & Zibit , 2014), we can observe several broad categories of credit rating determinants, such as assets, legal issues, or fund sufficiency. It is also mentioned that good management practice is an important prediction for favorable credit performance. In relation to the financial performance, Moody's credit analysts included the general fund balance or structural deficit as important financial factors. When government have unreserved or undesignated general fund balance, it means that there is a flexibility regarding the resource to support their policy, while deficit structure is an indicator of negative fund balances in the future (Ammarz et al., 2001).

The study from Ammarz et al. provides four factors that contribute to municipal credit rating, there are: economic growth, taxpayer wealth, city composition, and city's diversification (Ammarz et al., 2001). It is consists of the measurement of financial position, financial performance, leverage and liquidity.

Literature study in the corporate sector of accounting observes the relation between size and the quality of financial reports. The same thing happened in the governmental sectors, different studies are observed strong effect of size, while some show no significant relationship or even negative (Christiaens & Peteghem, 2007).

Focusing on general obligation bonds type, local government entity's capabilities that related to the debt burden can be measured by the availability of revenues to pay the debts (Hastie, 1972). In general these revenues is dominated by the tax. Consequently, it is suggested that municipalities with high tax revenue will more likely to have low debt burden.

In developing credit-rating model, debt ratios that representing government's debt burden are playing major role (Ammarz et al., 2001). The assessment of debt per capita is also important to measure debt burden, since this variable will provide the level of community capability to carry its debt burden. The hypothesis is a high ratio of debt burden per capita will associate to the low credit rating.

Another debt valuation is included to compare municipal regarding their net debts. This variable is determined by dividing total liabilities minus cash and cash equivalents with total assets. The net debt shows the riskiness of the government to settle their debts. A higher ratio may indicate that the muni bonds are not sufficiently supported by the underlying assets.

Previous study from Simonsen, Robbins, and Helgerson argues that small community typically has fewer resources to handle their financial management and tends to be less sophisticated. Population is also can be considered as proxy to measure economy differsification and potential market to release bonds. Another research shows that the rate of population growth represent public service demand and taxation base (Rubinfeld, 1973). The population data is obtained from the Census Bureau official estimation of the population for the cities and towns in New Jersey[1].

[1] Source: US Census Bureau B01003 http://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t#

This variable includes the income of the householders[2] and all other individuals above the age of 15 years old that live in the household, whether they are related to the householder or not. And because many households consist of individuals without family relation (marriage, adoption or birth), this variable is more typical representation of today condition instead limited only on family income. Median household income[3] can be a reasonable variable to predict future cash flow for offsetting outstanding debt or taxation income.

The municipal bonds payment will be made in the future, therefore, the need to estimate future ability to pay. One of the characteristics to determine the future capability is budgetary information. With better quality and educated of human resource, a local government is likely to maintain and increase its potential stability of income and resources (Hastie, 1972).

The budgetary information is obtained based on the guidelines of Flexible Chart of Accounts (FCOA) from the Department of Community Affairs. The first information that can be collected from the municipal budget form is anticipated revenue. This account shows the anticipated revenues from multiple sources to finance the local government annual budgets. Anticipated revenues are non-tax sources of funds, which guaranteed to be paid. Due the nature of certainty, this variable is good indicator of future cash inflow for the municipalities. This account can be classified into several sub accounts, namely: local revenue, state aid, federal and state grants and interlocal service agreements. Local revenue is revenue that generated locally while state aid is the revenues of municipalities that originated from the State of New Jersey. The federal and state grants are various grants that distributed by the

[2] We use household median income instead of family because based on the US Census description family media income is the income of a family that consists of two or more people (one of whom is the householder) related by birth, marriage, or adoption residing in the same housing unit. And analysts often use median household income to indicate what is typical.
[3] B19013 Source: http://factfinder2.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t

federal and state governments. And lastly, interlocal service agreement shows income from the shared service paid by other local governments.

In contrast to the revenues side, the expenditure will show appropriations in the format of line-by-line items in the municipal budget data sheets. Beside the operating expenses, there are major accounts of expenditures such as capital improvement, municipal debt services, and reserve for uncollected taxes that need to be analyzed. Operating expenses included various expense to finance the operating activities of the local government. Capital improvement is an account to record expenses that related to the projects that currently financed by the municipal budgets. For municipal debt services, it is included all expenses that related to the issuance and payment of municipal debts. And finally, reserve for uncollected tax represents the figure that backup the uncollected tax for the payment of various expenses such as school expenditures or municipal obligations. The majority of local government revenue is from tax. Therefore, incorporating uncollected tax in the model will provide the potential resources of government to fulfill their bonds in the maturity period.

2.1. Artificial Neural Network

Artificial Neural Networks (ANNs) mimicking the structure of biological neural network, which is based on the process and physiology of the nervous system. ANNs is simplify attempt to produce the learning and decision making of the brain (Lucchini & Pisati, 2005). The structure of ANNs comprise of three layers. The first layer is input that is consisting of inputs or variables. Following this layer is hidden layer, where every input will be multiplied by certain weights that refer to the variable strengths. The result of the hidden layer calculation will be shown in the last layer, which is the output layer.

ANN is a mathematical model that can make prediction based on variables input. The network in ANN refers to the pattern that connects the input, nodes (on the hidden layer), and outputs (Garson, 2014). Similar to the other prediction models, training set is essential to generate relationship between input and output result. The process that produces the predictive model based on the training set is called learning. The learning process is aiming to minimize the prediction error. After the neural network is created, then it can be used to make prediction.

Comparing to more conventional statistical methods such as regression, ANN provide several advantageous. The first advantage is the capability to estimate almost any nonlinear function (Fanning & Cogger, 1998). ANNs deliver robust result by ignoring irrelevant inputs and noise (Cortez, 2014). Related to the pattern recognition, ANNs is more effective then regression method (Coakley & Brown , 1993). Furthermore, it is also capable to provide a superior fit of prediction and detection method compare to linear time series models (Kim & Mayer, 2010). The main criticism of this method is the black box attribute. Due to the complexity of hidden layer process and calculation, some opponents of ANNs belief that this method is open to various adjustments and it is difficult to explain an underlying process for the relationship. However, the opposite opinions belief that black box is a user oriented, especially for those that do not have in-depth knowledge about the function modeled.

Multilayer perceptron (MLP) is a procedure in ANN architecture that aiming to minimize the prediction error of the output. MLP is well known as the predictive utility that can be applied into various fields (Garson, 2014). MLP model is also used in predicting values based on the training set data and this method is supervised learning. In sum, MLP is a procedure that produces a predictive model for one or multiple outcome variables based on the value of the predictor variables.

The structure of MLP is known as feed forward because the connection of the network is started with the input layer to the output layer without any feedback loops. Input layer consists of the predictors or variables. The hidden layer contains unobservable nodes or units. The value of these units is in part function of the predictor, the network characteristic, or user specifications. The output layer provides the responses, similar with the hidden layer, the value is depend on the various weights and functions.

3. Research Method

The design of this study, in part, is the adaptation of the classic research from Copeland and Ingram in 1982 (Copeland & Ingram, 1982), however it is differ in several aspects. First this study is implementing a machine learning technique, which is Artificial Neural Networks (ANN) instead of regression, hence various types of variables can be captured and non-linear analyses can be achieved. The second difference is that this research focuses on the impact of financial and non-financial attributes toward the change of credit rating and not the other way. Finally, deviation with the previous research is due to the sample selection. This study is attempting to capture subset of municipals or local government entities within the state of New Jersey to achieve similarity of accounting practice in the sample.

The bond in this study is general obligation bond (GO bonds), the reason of this selection is because the purpose of GO bonds are not issue specific hence comparability analysis from different type of issuance can be implemented (Ingram, Brooks, & Copeland, 1983). The input variables selection can be categories into two main groups, financial and non-financial (

Table 2). For the financial type of variables, it is attempting to capture the financial conditions of the local government. All these information can be collected from the CAFR, municipal budget or external sources such as Bloomberg. The non-financial variables consist of demographic information such as population rate or household median income. These variables are obtained from the US Census Bureau or local governments' websites.

The financial data is mainly collected from the basic financial information of CAFR and direct request to the municipal, while non-financial data sources are vary from the notes to financial statement to external parties, such as U.S. Bureau Statistic and Bloomberg. The sample is obtained from the cities or municipal in the state of New Jersey that issue bonds and financial statements within the period of 2008-2014. The type of the municipal bond is only includes General Obligation (GO) and excludes other types such as revenue bonds or housing authority bonds because these other types of bonds are required substantially different factor and analysis to determine their credit ratings. The dataset is divided into two parts, training set and test set. The training set is used to compute the weight of every input toward the outputs. After the weight and model are set, the test set will be used as the cross-validation or caliber the result of training set.

4. Results

The statistical software used in this paper is IBM SPSS Statistic and under neural network analysis, I select multilayer perceptron as the method. The S&P data set is divided into two part, 65% training and 35 for validate the model, which is the normal practice in the ANN research (Lucchini & Pisati, 2005). The result shows that this model is capable to predict the credit rating with accuracy more than 70%.

S&P credit rating is derived mostly from the CAFR (Financial Report) data, we can see on the Table 3 that the top ten of the most significant variable in the model is from CAFR.

Moody's dataset shows lower prediction capability compare to the previous data set. Based on the level significance of the independent variables, we can see the top 10 most significant in the model (Table 4) is different composition with S&P. Information from budget report and demographic is also included in the top ten with some of the CAFR variables.

Based on this model we observed the differences between two major credit rating agencies. S&P credit rating is more emphasis on the financial statement information and Moody credit rating is influenced by several factors such as budgetary information, demographic data, and some of the CAFR variables.

5. Conclusion and Limitation

This study is aiming to provide empirical evidence on the significance level of financial and non-financial factors in affecting the change of municipal bonds rating. Moreover, the result enables the understanding regarding which government's keys financial and non-financial information that influence the credit rating.

The result of this study is expected to provide users fundamental information regarding municipal bond credit ratings. By understanding the process and method of credit rating agencies we can trace back any discrepancy in the past or predict the future municipal bonds credit rating. It is also can be an additional insight of accounting and non-accounting information that are considered as part of credit rating agency assessments. The creditors or investors need the predictive information because their yield of investments depends on the change of credit rating.

The limitation of the model is that the observation is only focus on the New Jersey cities and towns. Furthermore, the result is also limited by the included variables, which means that others variables can derive different results.

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8. Table and Appendix

Table 1 The Summary of Major Municipal Credit Rating Agency

Classification	Moody's	S&P	Fitch
Best Quality	Aaa	AAA	AAA
High Quality	Aa1 Aa2 Aa3	AA+ AA AA-	AA+ AA AA-
Upper Medium Grade	A1 A2 A3	A+ A A-	A+ A A-
Medium Grade	Baa1 Baa2 Baa3	BBB+ BBB BBB-	BBB+ BBB BBB-

Table 2 Variable Summaries

Variable Number	Description
Financial Accounting-Information Source: CAFR	
V1	Total Revenues (t-1)
V2	Total Revenues
V3	Total Operating Expenses (t-1)
V4	Total Operating Expenses
V5	Net Change in Fund Balances (t-1)
V6	Net Change in Fund Balances
V7	Cash & Near Cash (t-1)
V8	Cash & Near Cash
V9	Total Assets (t-1)
V10	Total Assets
V11	Accounts Payable (t-1)
V12	Accounts Payable
V13	Total Liabilities (t-1)
V14	Total Liabilities
V15	Reserved for Encumbrances (t-1)
V16	Reserved for Encumbrances
V17	Reserved for Other (t-1)
V18	Reserved for Other
V19	Unreserved General Fund (t-1)
V20	Unreserved General Fund
V21	Total Fund Balances (t-1)
V22	Total Fund Balances
V23	Property Tax Revenues (t-1)
V24	Property Tax Revenues

Variable Number	Description
V25	Miscellaneous Revenues (t-1)
V26	Miscellaneous Revenues
V27	General Government Expenses (t-1)
V28	General Government Expenses
V29	Salaries and Employees Benefits (t-1)
V30	Salaries and Employees Benefits
V31	Other Program Expenses (t-1)
V32	Other Program Expenses
V33	Capital Outlay (t-1)
V34	Capital Outlay
V35	Principal Debt Service (t-1)
V36	Principal Debt Service
Budgetary Information Source: Municipal Data Sheet	
V37	Total Anticipated General Revenue
V38	Total Anticipated General Revenue (t-1)
V39	Surplus Anticipated Revenues: A portion of Fund Balance (surplus) that utilized as revenue to support the current budget
V40	Surplus Anticipated Revenues: A portion of Fund Balance (surplus) that utilized as revenue to support the current budget (t-1)
V41	Total Section A/Local Revenues: Revenues that generated locally
V42	Total Section A (t-1)/Local Revenues (t-1): Revenues that generated locally (t-1)
V43	Total Section B/State Aid without Offsetting Appropriation: General aid and grants from the State of New Jersey
V44	Total Section B (t-1)/State Aid without Offsetting Appropriation (t-1): General aid and grants from the State of New Jersey (t-1)
V45	Total Section C/Dedicated Uniform Construction Code Fees Offset with Appropriations: Revenues that assigned to support the code enforcement budget to maintain the safety regulations and health standards are upheld.
V46	Total Section C (t-1)/Dedicated Uniform Construction Code Fees Offset with Appropriations: Revenues that assigned to support the code enforcement budget to

Variable Number	Description
	maintain the safety regulations and health standards are upheld (t-1).
V47	Total Section D/Shared Services Agreements: Revenues that received for shared services paid by other localities.
V48	Total Section D (t-1)/Shared Services Agreements: Revenues that received for shared services paid by other localities (t-1).
V49	Total Section E/Additional Revenues
V50	Total Section E (t-1)/Additional Revenues (t-1)
V51	Total Section F/Public and Private Revenues: Funds to be spent on specific purposes
V52	Total Section F (t-1)/Public and Private Revenues: Funds to be spent on specific purposes (t-1)
V53	Total Section G/Other Special Items
V54	Total Section G (t-1)/Other Special Items (t-1)
V55	Receipts from Delinquent Taxes: The sum of delinquent taxes anticipated as revenue in the current year budget
V56	Receipts from Delinquent Taxes (t-1): The sum of delinquent taxes anticipated as revenue in the current year budget (t-1)
V57	Amount to be Raised by Taxes for Support of Municipal Budget
V58	Amount to be Raised by Taxes for Support of Municipal Budget (t-1)
Demographic Information Source: US Census	
V59	Population
V60	Median Household Income

Table 3 S&P Variables

No.	Variable Type	Description
1	CAFR	Unreserved General Fund
2	CAFR	Salaries and Employees Benefits
3	CAFR	Reserved for Other
4	CAFR	Total Fund Balances
5	CAFR	Total Assets
6	CAFR	Total Liabilities
7	CAFR	Property Tax Revenue
8	CAFR	Other Tax Revenues
9	Budget	Tax Revenue for Budget
10	CAFR	Accounts Payable

Table 4 Moody's Variable

No.	Variable Type	Description
1	Budget	Anticipated Revenue-Additional
2	Budget	Anticipated Revenue-Total
3	Demographic	Median Household Income
4	Budget	Anticipated Revenue-Assigned
5	CAFR	Operating Expenses-Total
6	Budget	Anticipated Revenue-Surplus
7	Budget	Anticipated Revenue-delinquent taxes
8	CAFR	Property Tax Revenue
9	CAFR	Cash and Near Cash
10	CAFR	Miscellaneous Revenues

Appendix 1 S&P

Case Processing Summary

		N	Percent
Sample	Training	210	66.0%
	Testing	108	34.0%
Valid		318	100.0%
Excluded		1	
Total		319	

Model Summary

Training	Cross Entropy Error	150.850
	Percent Incorrect Predictions	24.8%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.14
Testing	Cross Entropy Error	82.580
	Percent Incorrect Predictions	26.9%

Dependent Variable: Sim_Credit Rating

a. Error computations are based on the testing sample.

Classification

Sample	Observed	Predicted			
		1	2	3	Percent Correct
Training	1	0	35	0	0.0%
	2	0	158	0	100.0%
	3	0	17	0	0.0%
	Overall Percent	0.0%	100.0%	0.0%	75.2%
Testing	1	0	15	0	0.0%
	2	0	79	0	100.0%
	3	0	14	0	0.0%
	Overall Percent	0.0%	100.0%	0.0%	73.1%

Dependent Variable: Sim_Credit Rating

Appendix 2 Moody's Statistical Results

Case Processing Summary

		N	Percent
Sample	Training	234	74.1%
	Testing	82	25.9%
Valid		316	100.0%
Excluded		1	
Total		317	

Model Summary

Training	Cross Entropy Error	176.657
	Percent Incorrect Predictions	38.5%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.13
Testing	Cross Entropy Error	62.443
	Percent Incorrect Predictions	36.6%

Dependent Variable: Sim_Credit Rating

a. Error computations are based on the testing sample.

Classification

		Predicted			
Sample	Observed	1	2	3	Percent Correct
Training	1	0	6	2	0.0%
	2	0	85	32	72.6%
	3	0	50	59	54.1%
	Overall Percent	0.0%	60.3%	39.7%	61.5%
Testing	1	0	2	0	0.0%
	2	0	32	10	76.2%
	3	0	18	20	52.6%
	Overall Percent	0.0%	63.4%	36.6%	63.4%