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Predicting Business Failure Through The Use of Machine Learning and Local Government Administrative Datasets

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Abstract

Local governments generate an enormous amount of data about properties within their jurisdiction simply through day-to-day administrative activities. For example, code enforcement violations are recorded and available in nearly every local municipality, often dating back many years or even decades. Using a variety of these administrative datasets, we aim to identify a novel methodology for predicting business failures. Local administrative datasets from the City of Kalamazoo, Michigan were utilized to test the predictive power of multiple models, including logistic regression, one-class support vector machine, and a cross-validated ensemble of random forests. Our initial results show promise in being able to identify a significant portion of failed businesses. Our models sought to optimize the number of failed businesses correctly predicted rather than pure accuracy. This goal was driven by the potential applicability of such a model to business support and intervention strategies. In addition to this positive preliminary result, we found significant relationships between business failure and specific predictors, including property tax delinquency, code enforcement violations, failed inspections, and specific types of 911 calls. We will discuss considerations for improving data collection at the local government level, next steps for future modeling work, and potential applicability of such a model for local government staff and others.

1. Introduction

Predicting business failure through the use of data is no new idea. Banks and business entities themselves have a significant stake in being able to identify what businesses are on an upward trajectory and which are more likely to fail. However, this analysis has long relied on the use of internal financial data about the performance of a given individual company (e.g., profit and loss ratios, cash flow projections, market viability, competition, etc.). This paper proposes a new approach for identifying what businesses may be at-risk of failure through the use of administrative data gathered and maintained by nearly every local government in the United States. Data regarding code enforcement violations, inspections, permits, property taxes, assessing, ownership information, utility bill payments, crime, fire and EMS calls, and other data all could be used as "predictors" of businesses that may be struggling.

By using these administrative datasets in combination with historical data about known businesses that have "failed" between 2014-2017 in the City of Kalamazoo, MI, we will attempt to present a novel method for identifying at-risk companies. Using supervised machine learning techniques, we will determine if the administrative datasets collectively offer predictive value into identifying businesses that are at-risk of failing. If the model shows promise, additional research, datasets, and potential interventions will be investigated to hopefully target key resources to support these at-risk businesses through my current role working as a Data Analyst for the City of Kalamazoo, Michigan.

1.1 Literature on Business Failure Prediction

As mentioned previously, substantial research and existing efforts exist to identify businesses that might be at risk of failure. "Over the last 35 years, the topic of business failure prediction has developed into a major research domain within corporate finance. Many academic studies have been dedicated to finding the best corporate failure prediction model" (Balcaen and Ooghe, 2006). Most of the previous work in this area is focused on predicting business failure through the use of company financial information and financial ratios (source). This is reasonable for large financial institutions that have regular access to this data through their role as a financier of business ventures. Some of this data is also publicly available for companies that are required to report such data (publicly-traded [i.e., large] companies), however, for smaller businesses and for non-financial institutions, conducting any sort of business failure prediction is very difficult. As such, this study is unique in the sense it attempts to provide a methodology that relies on readily available administrative data maintained by nearly all local municipalities.

The explosion of digital technology products and uses through the “big data” advancement over the last decade or so has reshaped the conversation for utilizing non-traditional datasets to predict or assess a wide variety of outcomes. Wang et al. (2015) fit this realm through their model for predicting ”business failure” through the use of Foursquare mobile local-based checkin data for restaurants in New York City. While the dataset utilized was novel, their study was limited by their definition of ”business failure”, which they chose to be any company that had less than 1 Foursquare checkin per day during their study period.

The present study proposed in this paper differs because it has the benefit of utilizing historical data about businesses that are known failures through the use of a dataset on personal property tax accounts in Kalamazoo. The dataset is separated into active and inactive accounts, and also provides information on delinquent tax payment over the years of 2014-2017. The inactive accounts are either those that are no longer in business or that moved out of Kalamazoo (i.e., as a result, their Kalamazoo personal property tax account is no longer active). Either case is meaningful as an account of “failure” from the City of Kalamazoo’s perspective, keeping businesses in the City and healthy is critical to the overall health and tax base of the City. This dataset will be used retroactively to compare historical business failure data to historical administrative datasets to test the predictive power of several variables to determine if we can identify the failed businesses with meaningful accuracy.

2. Data Preparation

While business success and failure is a common area of concern for municipalities around the world, standard and readily available data on business failures is often not in place. In addition, local governments tend to maintain datasets in several different formats, with varying location identifiers and data input processes. The data used in this analysis from the City of Kalamazoo included the following:

- **Tax Data**: Personal property tax account list with active and inactive accounts and personal property tax delinquency list with information on which accounts were delinquent or late on their tax payments in a given year
- **Building Department Data**: Code enforcement cases, permits issued, and inspections
- **Assessing and Property Characteristic Data**: Property ownership, zoning, assessed and taxable value information
- **Public Safety Data**: 911 calls for Fire, EMS, Police, and non-emergency

Data between the years of 2013 and 2017 from each dataset was gathered and prepared for analysis. A challenge with this phase was the fact that some datasets reference something occurring at a given parcel of land, some at a specific business, some at a given address (several businesses may share an address), and some at latitude / longitude coordinates.

The desired output of this preparatory work to merge various administrative datasets was a comprehensive understanding of “what occurred” (e.g., a permit was issued, a 911 call, an inspection) at a given location in a given year. Ultimately, connections between datasets were imperfect and not all data from each dataset could be reliably connected to the comprehensive dataset. However, the resulting dataset for prediction contains a vast majority of the “activity” from 2013-2017 for each active and inactive business in our list.

2.1 Final Dataset and Predictors

The final dataset allows for binary classification modeling of active and inactive businesses by year within the City of Kalamazoo. In particular, there are 194 identified businesses that became inactive between the years of 2014 and 2016. Of these, 100 were identified as going inactive in 2014 (i.e., their last personal property tax payment was 2014), 52 went inactive in 2015, and 42 went out in 2016. There are an additional 11 businesses that have confirmed their last year of activity will be 2017. Next, there are 2,450 total active businesses, of which 984 we know have been active since 2014 (they made a payment in 2014), an additional 153 made a payment in 2015, and 168 more made their first “known” payment in 2016. This means that 1,305 total businesses have a registered personal property tax payment since 2014, and that 1,145 businesses are classified as “active” but don’t have any payments from 2014 to 2016. These businesses may simply be tax exempt, but because we don’t have a sense for the year they became active, they are excluded from the analysis. This information and the resulting year by year prediction datasets is summarized in Figure 1.

	Inactive	Active and First Payment Was This Year or Earlier	Percent Inactive
2014 Failure Prediction	100	984	10.2%
2015 Failure Prediction	52	1,137 (153 net new)	4.6%
2016 Failure Prediction	42	1,305 (168 net new)	3.2%
Total	**194**	**1,305**	

Figure 1: Summary of Active and Inactive (Failed) Businesses by Year

The following variables were developed from the initial raw data files to be used in the predictive models:

- **Inactive**: Whether or not the business is an active or inactive record
- **Active Year and Inactive Year**: Whether or not the business became active or inactive in 2014, 2015, or 2016
- **DDA and TIF**: A set of binary variables indicating whether a given business is located in the City's Downtown Development Authority (DDA) or Tax Increment Financing (TIF) districts
- **Number of Enforcement Cases**: A set of numeric variables that indicate the number of code enforcement cases at a given location. Separate variables for each year from 2013-2016
- **Number of Permits**: A set of numeric variables that indicate the number of permits issued at a given location (variable for each year from 2013-2016)
- **Amount Billed for Permits**: A set of numeric variables that indicate the total amount of dollars billed for permits issued at a given location (variable for each year from 2013-2016)
- **Total Inspections, Inspections Failed, and Percent of Inspections Failed**: A set of numeric variables that indicate the total number of inspections, number of inspections that required another visit (i.e., failed), and the percent of total inspections that failed (variables for each year from 2013-2016)
- **SEV and TV**: The State Equalized Value (SEV) and Taxable Value (TV) of a given location (variables for each year from 2013-2016)
- **SEV and TV Growth**: Binary variables indicating whether or not the SEV or TV increased from the previous year (variables for each pair of years from 2013-2016. For example, variable name "TVGrowth13_14
- **Owner in City and Ownership Changes**: Binary variables indicating whether or not the owner of a given property is located in Kalamazoo for each year and variables indicating ownership changes from year to year (for each year from 2013-2016)
- **Zoning and Zoning Change**: Variables indicating the zoning district a given business is located within and if the zoning of a particular business changed from year to year (for each year from 2013-2016)
- **Delinquent Personal Property Tax Payments**: Binary variables indicating whether or not a business owner was delinquent on their personal property tax payments in a given year (for each year from 2013-2016)
- **911 Calls at and in Proximity to Business**: Variables that show the number of 911 at a specific location and within 500 feet of a business' property by type, including calls for violent crimes, auto-related crimes, fire-related calls, property related calls, and misc./other calls (for each year from 2013-2016)

Altogether, a subset of these variables for a given year was utilized to predict which businesses failed the following year. For example, if a given business had multiple 911 calls, failed inspections, an ownership change, and did not see their property values increase, they may be more likely to fail than a business that did not have such factors. These are the sorts of relationships tested through the present paper.

2.2 Summary Statistics

Following are some summary statistics to compare general characteristics of active and inactive (i.e., 'failed') businesses for each year in the analysis.

	Active Businesses				Failed Businesses			
Variable	**2014**	**2015**	**2016**	**Avg.**	**2014**	**2015**	**2016**	**Avg.**
% in the DDA	18.2%	19.0%	18.7%	18.63%	30.0%	21.1%	16.7%	**22.6%**
% Delinquent on Pers. Prop. Tax	19.6%	19.8%	16.9%	18.77%	42.0%	24.5%	23.3%	**29.9%**
Avg. # of Code Enf. Cases	0.16	0.12	0.14	0.14	0.24	0.10	0.05	0.13
Avg. # of Permits	1.22	1.0	0.97	1.06	0.56	1.50	0.42	0.83
Avg. % of Inspections Failed	10%	7.8%	6.3%	8.03%	8.6%	8.9%	1.5%	6.3%
Avg. SEV	$358,172	$346,100	$351,664	$351,978	$70,486	$333,356	$150,560	**$184,801**
Avg. TV	$353,634	$333,356	$339,675	$342,221	$68,805	$328,015	$148,893	**$181,904**
% of Businesses with Increase in SEV from Previous Year	54.8%	34.0%	31.8%	40.20%	33.6%	26.4%	27.9%	**29.3%**
% of Businesses with Increase in TV from Previous Year	54.8%	41.6%	40.8%	45.73%	34.6%	33.9%	37.2%	**35.2%**
% of Owners in Kalamazoo	62.2%	62.0%	64.5%	62.90%	70.3%	62.3%	65.1%	65.9%
% of Businesses with Ownership Changes from Previous Year	8.0%	8.9%	7.4%	8.10%	5.0%	9.4%	7.0%	7.13%
Avg. # of Auto-Related 911 Calls	0.18	1.12	1.08	0.79	0.40	2.11	0.79	**1.10**
Avg. # of Auto-Related 911 Calls within 500 feet	58.85	43.43	42.54	48.27	56.74	44.38	38.79	46.64
Avg. # of Fire-Related 911 Calls	0.13	0.90	0.87	0.63	0.02	1.67	0.47	**0.72**
Avg. # of Fire-Related 911 Calls within 500 feet	6.27	4.98	4.58	5.28	5.08	7.15	4.09	5.44
Avg. # of Property-Related 911 Calls	0.46	3.26	3.54	2.42	0.13	7.96	1.79	**3.29**
Avg. # of Property-Related 911 Calls within 500 feet	36.09	37.69	40.38	38.05	33.16	43.96	43.95	40.36
Avg. # of Violent Crime 911 Calls	0.21	1.62	1.67	1.17	0.07	4.23	0.85	**1.72**
Avg. # of Violent Crime 911 Calls within 500 feet	20.43	18.96	19.75	19.71	17.20	23.06	18.38	19.55

Figure 2: Summary statistics of predictors of active and failed businesses by year

In summary, we found that active businesses and failed businesses differ in respect to a variety of our predictors. In particular, a greater proportion of failed businesses are located in the downtown (DDA), were delinquent on their personal property taxes, had lower SEV and TV, didn't see increases in SEV and TV as often, and had more 911 calls of every type analyzed at their location. Failed businesses also had less permits issued on average compared to active businesses and are slightly more likely to have their owner in Kalamazoo. These relationships show the initial promise in developing a predictive model that can reliably identify the distinction between an active business and one that is no longer active.

3. Methodology

In addition to the summary statistics that give a sense of the relationship between the independent variables and business failure, a number of specific statistical models were developed to test the predictive power of this data. In each case, three iterations of each model were run, one using 2013 data to predict failures in 2014, one using 2014 data to predict failures in 2015, and one using 2015 data to predict failures in 2016. The three models used were logistic regression (or a 'logit' model), a one-class support vector machine model, and cross-validated random forest models. These models were all chosen for their strengths in classification modeling, and in particular in relation to binary classification. In addition, the unique structure of our dataset, being substantially imbalanced (i.e., significantly more active businesses than inactive each year) required the use of this ensemble of machine learning techniques best suited to handle this kind of problem. An overview of each modeling technique used is provided here.

3.1 Logit Model

The logit model is commonly used across many disciplines when the core task at hand is to predict a binary outcome variable based on a set of predictors. It has been used regularly as a technique for business failure prediction and modeling (Altman & Saunders 1998, Vuran 2009, Wang et al. 2015). The outcome of a logit model provides a probability estimate for how likely a record (in our case a business) is to be classified as either a ‘1’ or a ‘0’. At this point, cutoff values are chosen to transform these probabilities into binary classifications. Although, the probabilities themselves are useful to get a sense of what businesses the model has classified most strongly as likely to fail or most likely to stay active. Our first run through will utilize a probability estimate of 0.5 as the cutoff to classify a business as a likely Inactive, though we’ll use a few other cutoffs as well to see if we can improve performance. We utilized two “optimized” cutoff points for each iteration of the logit model, one that optimizes both the number of actives and inactives correctly predicted, and one that optimizes the sensitivity (i.e., recall) only. We’ll utilize the specificity, sensitivity, precision, accuracy, and F1-Score to evaluate performance of our logit models for each year (Alice 2015).

3.2 One-Class Support Vector Machine

In machine learning, support vector machines (SVMs) are what are known as supervised learning models. Supervised models can be used when there is some data that is already classified, and then we use that data to train to model to make a prediction on unclassified data. Unlike a logit model, the resulting classification is not probabilistic, and rather provides a simple binary classification output (Cortes and Vapnik 1995). One-Class SVMs are a particular version of an SVM designed for anomaly detection. This is useful in situations where, “you have a lot of ‘normal’ data and not many cases of anomalies you are trying to detect” (Microsoft 2017). In a One-Class SVM, the model is trained using only one of the classes of data (often the ‘normal’ class) and then when the abnormal class is fed in, the model attempts to detect these outliers because they should be dissimilar to the normal class. To evaluate the One-Class SVM performance, we’ll utilize specificity, sensitivity, precision, accuracy, and the F1-Score.

3.3 Random Forest with Cross-Validation

The final modeling approach employed was also the most complex. We employed and compared five variants of a 10 x 10 repeated cross-validated Random Forest model using a standard approach, under-sampling, over-sampling, Random Over-Sampling Examples (ROSE), and Synthetic Minority Over-Sampling Technique (SMOTE). A Random Forest operates as an ensemble learning method for classification that uses multiple decision trees to train the data and outputs the mode of the class of the trees in aggregate (hence the name 'forest').

These variations of the standard Random Forest are designed to help deal with problems of imbalanced data. With under-sampling, a random subset of samples from the 'normal' class are chosen to match the number of abnormal cases. Here, we risk losing valuable information from the active businesses in our dataset. With over-sampling, we randomly duplicate known failed businesses so that the number of failures matches the number of active businesses. The risk with this method is that of overfitting the model as a result of such duplications. To address the problems with both regular over- and under- sampling, we also tested some hybrid techniques. ROSE and SMOTE are two of the most common hybrid techniques. ROSE generates artificial balanced samples according to a smoothed bootstrap approach that aids estimation and accuracy evaluation of imbalanced classification problems (Lunardon et al. 2014). SMOTE is a hybrid technique that combines synthetic over-sampling of the abnormal class and under-sampling the normal class to achieve better classification performance (Chawla et al. 2002). The performance of each of these techniques is evaluated through the use of Sensitivity, Specificity, Precision, Accuracy, and the F1-Score (Glander 2017).

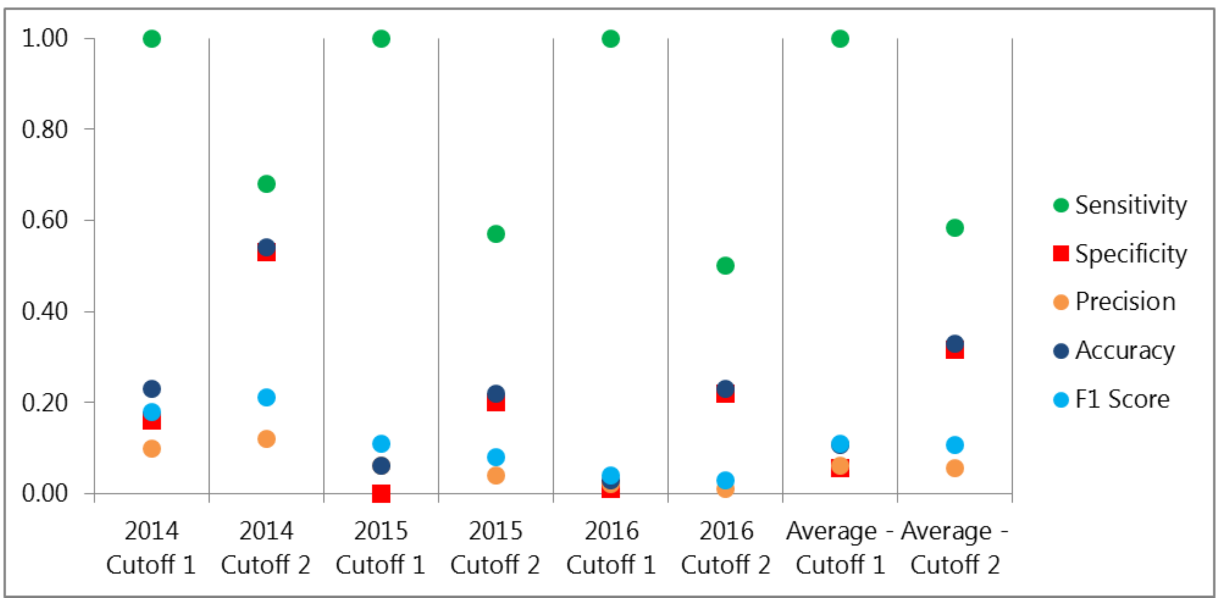
4. Results

Each modeling technique was employed to predict business failures in 2014, 2015, and 2016. An average of our five evaluation metrics was calculated to determine the performance of each model over the course of the three years. In evaluating the models, the optimization of Sensitivity and F1-Score are top priority. A brief overview of performance of each modeling technique is provided below, followed by an overall comparison of each of the three techniques.

4.1 Logit Model Performance

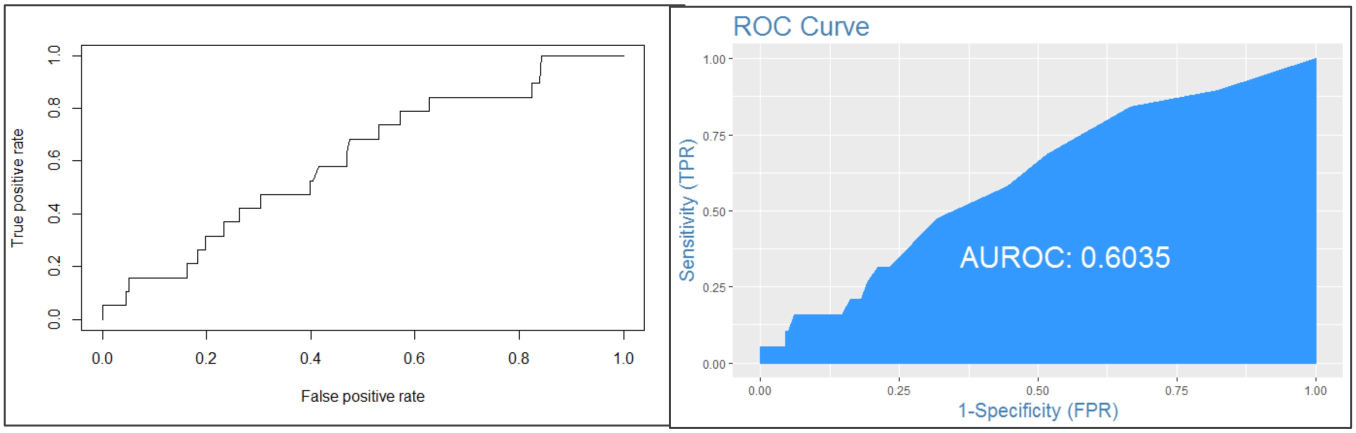
As mentioned previously, two optimized cutoff points were utilized in our logit model predictions for each year of the model. The performance of these variants are provided in Figure 3 below.

Figure 3: Performance of logit model variations by year



As you can see, the first threshold cutoff point optimized the sensitivity of the model, and was in a sense flawed by attempting to correctly classify every single inactive business. The second cutoff that optimized both actives and inactives overall provides some promising results. This model, on average over the course of the three years of predictions had a sensitivity of 0.58, specificity of 0.32, precision of 0.06, overall accuracy of 0.33, and F1-Score of 0.11. Finally, the various logit models found statistically significant relationships between failed businesses and delinquency on personal property taxes, increased code enforcement cases, failed inspections, property-related 911 calls, lack of SEV growth, and violent 911 calls. Figures 4 and 5 show the relationship between the true positive rate and false positive rate and the AUC for the 2014 logit model in particular.

Figures 4 and 5: False positive and true positive rate curve (left) and the AUC (right) of the 2014 logit model



4.2 One-Class SVM Model Performance

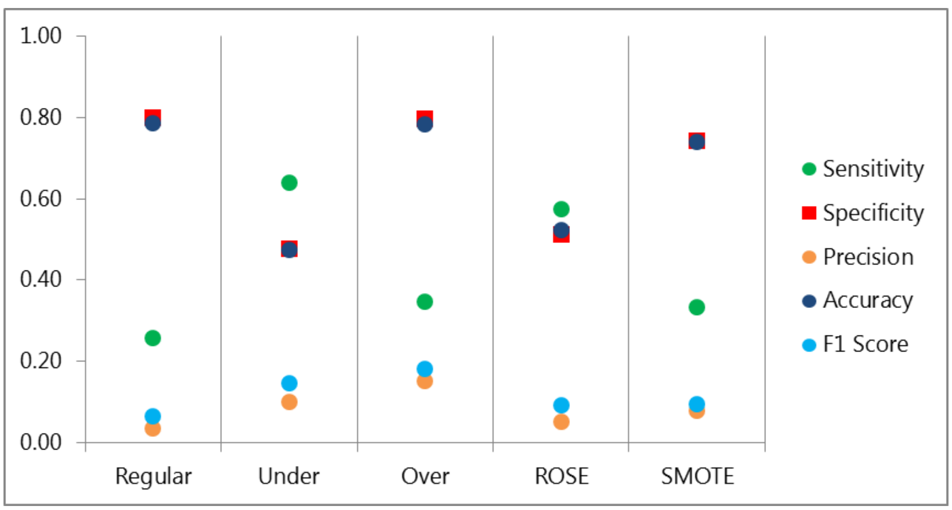
The One-Class SVM Model relied on training the model on only active businesses and then feeding the entire data set into the model for anomaly detection of inactives. The results were again moderately promising (see Figure 6).

Figure 6: One-class SVM performance by year

On average, the model maintained a sensitivity of 0.45, specificity of 0.50, precision of 0.05, overall accuracy of 0.50, and F1-Score of 0.09.

4.3 Random Forest Model Performance

The Random Forest technique relied on a 10 by 10 cross-validation and five different variants for prediction within each year. We utilized a standard approach, under-sampling, over-sampling, ROSE, and SMOTE techniques and compared each using sensitivity, specificity, precision, accuracy, and F1-Score. The average results of each model are included in Figures 7 and 8. What we found was that overall the under-sampled and over-sampled random forest models show the most promise for this particular classification task. The under-sampled model has the highest sensitivity on average, while the over-sampled model has the highest precision and F1-Score of any of the models tested.

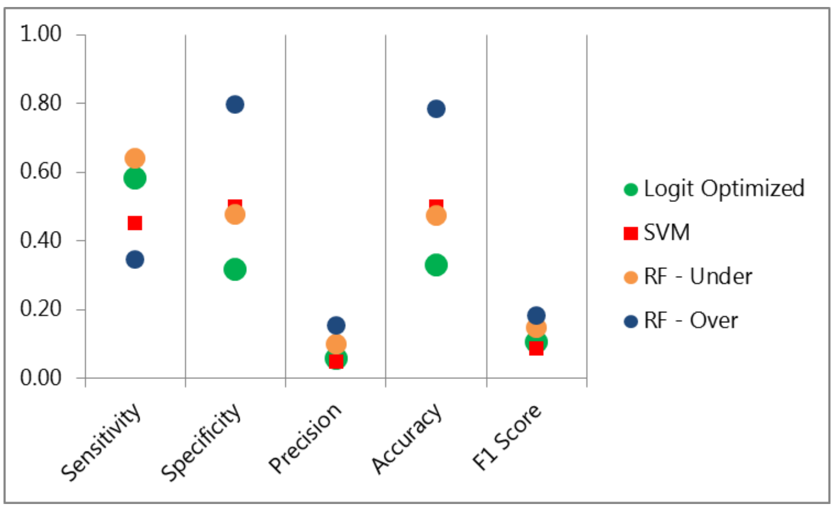


	Average Performance -- Random Forest Models				
Measure	**Regular**	**Under**	**Over**	**ROSE**	**SMOTE**
Sensitivity	0.26	0.64	0.35	0.57	0.33
Specificity	0.80	0.48	0.80	0.51	0.74
Precision	0.04	0.10	0.15	0.05	0.08
Accuracy	0.79	0.47	0.78	0.52	0.74
F1-Score	0.07	0.15	0.18	0.09	0.10

Figures 7 and 8: Graph (top) and table (bottom) of average performance of the random forest model variants

4.4 Summary and Comparison of Models

Figures 9 and 10 show the average performance of the most promising models tested, the logit model using a threshold to optimize both active and inactive classification, the SVM one-class model, and the random forest under- and over-sampled models. Each of these four models has various strengths depending on the desired outcome of the prediction. For example, the optimized logit model offers a relatively high sensitivity but the lowest overall accuracy of any of these models while the over-sampled random forest model offers both the highest specificity, precision, accuracy, and F1-Score. The over-sampled model's only weakness is its low sensitivity, which was a high priority performance measure for this task, as we wanted to primarily focus on classifying a high share of the inactives correctly.



	Average Performance – Best Models			
Measure	Logit Optimized	SVM	RF - Under	RF - Over
Sensitivity	0.58	0.45	0.64	0.35
Specificity	0.32	0.50	0.48	0.80
Precision	0.06	0.05	0.10	0.15
Accuracy	0.33	0.50	0.47	0.78
F1-Score	0.11	0.09	0.15	0.18

Figures 9 and 10: Graph (top) and table (bottom) of average performance of the best performing models from each modeling technique

5. Discussion & Future Work

The desired performance of our models is not necessarily to have a high accuracy, as this could be an indication of simply classifying all active companies correctly and misclassifying the inactives, which is where the real value potentially lies. We are interested in models that classify the most inactives correctly, even if it provides a large amount of actual actives incorrectly classified as inactive. This is because from an intervention standpoint, identifying failures and a list of businesses that have the characteristics of failures will be extremely useful. Using this model in the future to predict businesses that 'may fail', this would allow for an immediate prioritization of resources to the companies identified as potential inactives by the model. For this use case, four specific variations show promise, the optimized logit model, the one-class SVM, and the over- and under-sampled Random Forest models. All would allow for meaningful predictions of potential "failures" into the future. Such a list of potential failures could be used by local governments, banking institutions, and nonprofits to either prioritize businesses for support services and training, or to know which businesses to be wary of when it comes to investment. For investment prediction purposes, this model is not quite as reliable as models that have been in use for the past decades that rely on internal financial information, however, the novel use of the datasets presented in this paper show some promise as additional factors to consider in predicting business failure.

Future work on this effort to predict business failures using local government administrative data could potentially be improved in two ways; new or modified statistical modeling approaches and the inclusion of additional predictors and improved data. The field of machine learning and predictive modeling offers a vast array of tools and techniques that are constantly evolving. This paper evaluated the use of three such techniques and attempted to optimize them for the prediction case at hand, however we recognize there are many additional methods to test. Next, we recognize that the datasets utilized are not all-inclusive when it comes to potential publicly-available information about companies to include. We utilized datasets on a number of features including code enforcement, permitting, assessing and ownership, tax payments, and 911 calls. However, additional datasets from online review/check-in websites such as Yelp, YellowPages, or FourSquare could also be included. There are plenty of additional sources of information about companies both open and closed that ought to be investigated for their predictive power. Finally, a number of data preparation challenges were encountered during the completion of this project due to the messy and incompatible nature of datasets within even a single local government. These data consistency and compatibility issues present both a challenge but also a unique opportunity for improvement that could result in a much improved ease of use for future work. Local governments sit on a mountain of data that can provide great insight, only if it is structured in a format suitable for efficient analysis.

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