Can Machine Learning Algorithms Better Help Predict Fiscal Stress in Local Governments?

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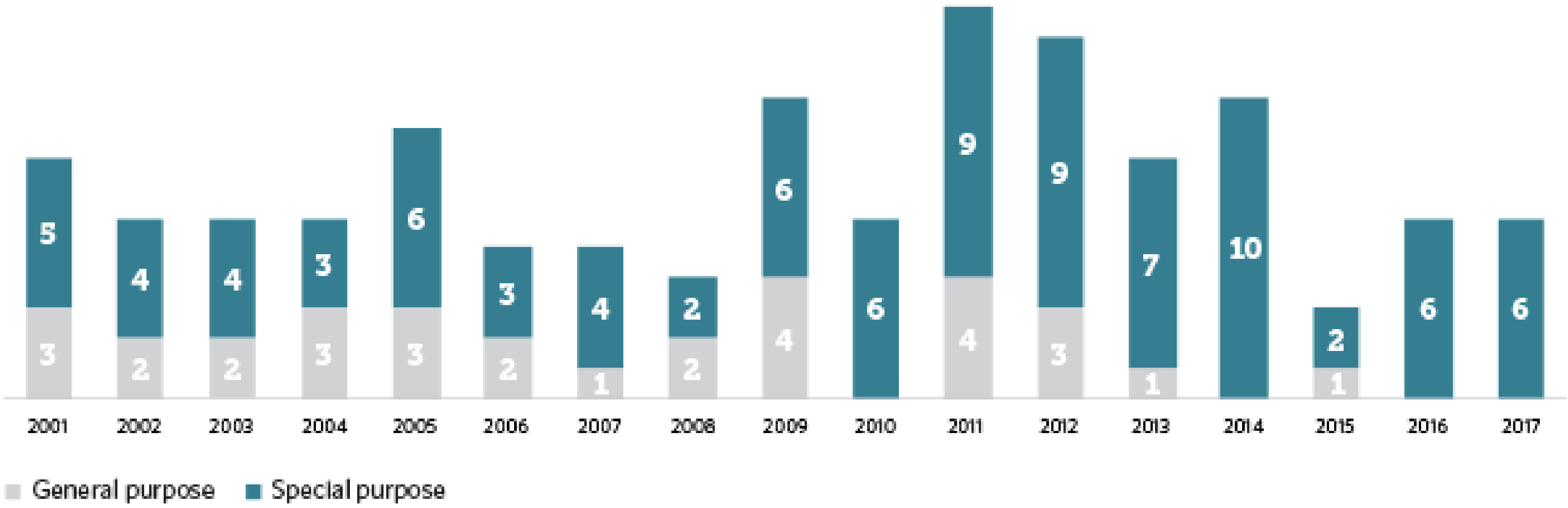
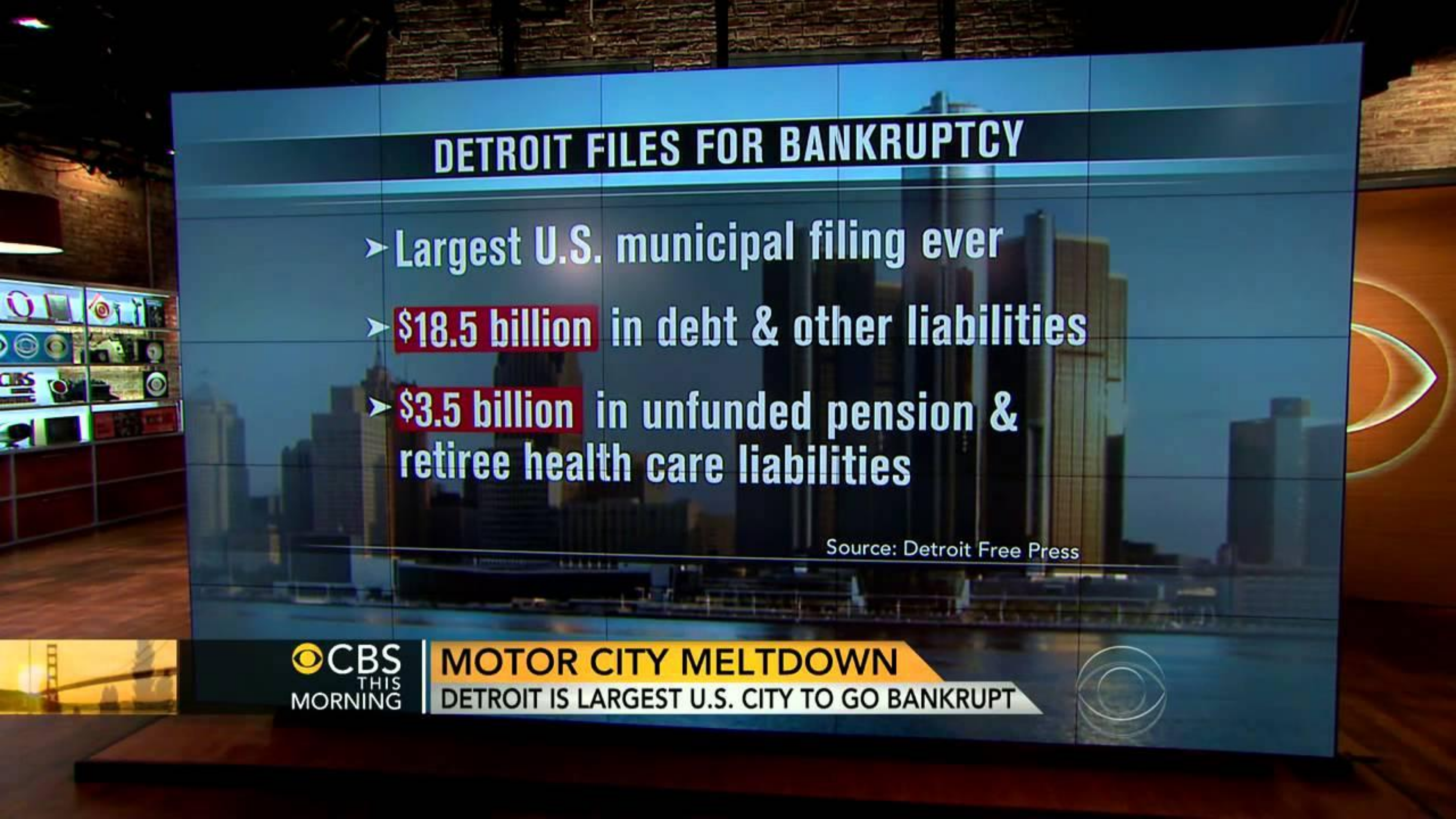
Figure 1

Chapter 9 Bankruptcy Filings, 2001–17

123 local governments have filed for bankruptcy since 2001



Note: Pew analysis of Public Access to Court Electronic Records data as of December 2017. Puerto Rico was not included in this count.

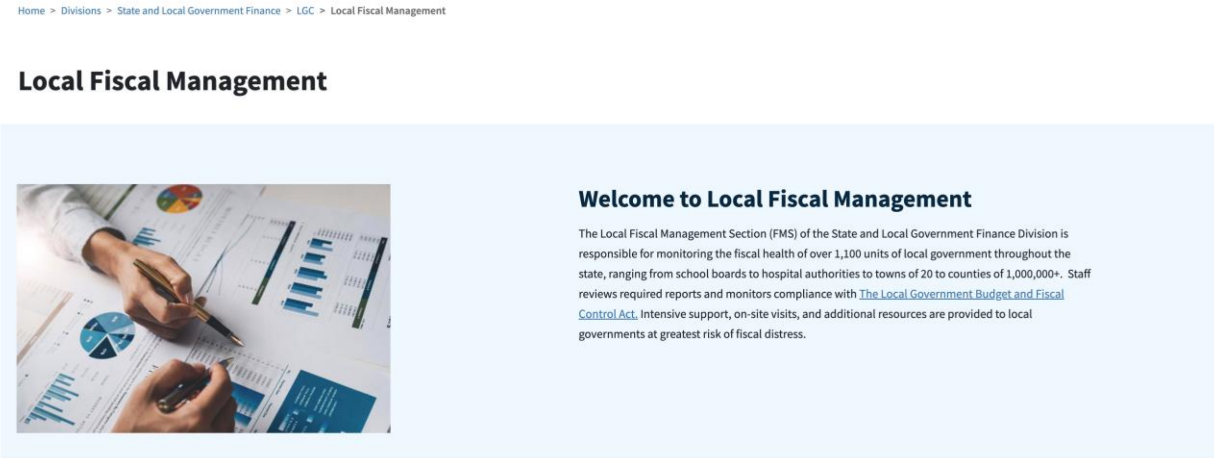

DETROIT FILES FOR BANKRUPTCY
Largest U.S. municipal filing ever
$18.5 billion in debt & other liabilities
$3.5 billion in unfunded pension & retiree health care liabilities
Source: Detroit Free Press
CBS THIS MORNING
MOTOR CITY MELTDOWN
DETROIT IS LARGEST U.S. CITY TO GO BANKRUPT

Research Motivation I

The Need to Detect Fiscal Stress as Early as Possible

- Fiscal stress poses a significant and recurrent challenge for local governments in the U.S.
- Fiscal stress can significantly impact the delivery of essential public services and the well-being of local communities.

Research Motivation II



Research Motivation II

The Complexity of Predicting Fiscal Stress

- In the real world, the dynamics preceding fiscal stress are most likely very complex
- Simple linear or threshold models may struggle to capture the complexities of fiscal phenomenon.

Research Motivation III

The Appeal of Using Machine Learning to Predict Fiscal Stress

- ML algorithms can uncover complex and nonlinear relationships
- ML algorithms can deal with rare events (fiscal crises)
- ML algorithms can optimally solve the trade-off between model underfitting and overfitting

Review of Relevant Literature

Extant Studies

- **Cross-Country Analysis**
  - Savona et al. (2015), Jarmukska (2021), and Moreno Badia et al. (2020), Hellwig (2021): random forest to predict country-level fiscal crises.
  - Fioramanto (2008): artificial neural networks to predict sovereign debt crises.

- **Subnational Analysis**
  - Antulov-Fantulin et al. (2021): Gradient Boosting Machines (GBM) to analyze Italian municipalities and find that non-financial variables like geographical location and socio-demographic characteristics significantly influence fiscal outcomes.

Review of Relevant Literature (Cont'd)

Traditional Approaches of Predicting Fiscal Stress/Crises

- **Early Warning Systems and Signaling Approach** (Liu et al., 2021)
  - Select several leading indicators of fiscal stress
  - Set pre-determined threshold values for each indicator
  - When an indicator crosses its threshold, it signals potential fiscal stress

- **Rely on traditional econometric models** (Fioramanti, 2008; Sarlin, 2014)
  - OLS: Linear regression models
  - Logit: Binary outcome models
  - Probit: Binary outcome models

Review of Relevant Literature (Cont'd)

Traditional Approaches of Predicting Fiscal Stress/Crises

- **Key Limitations:**
    - Retrospective focus
        - Often based on past data, limiting real-time adaptability
    - Risk of overfitting
        - Especially when using limited historical data and many predictors
    - Linear Assumptions
        - Cannot capture nonlinear, complex, or interacting predictors
    - Low Out-of-Sample Performance
        - Models often perform poorly when applied to new data

Review of Relevant Literature (Cont'd)

The Advantages of ML

- Superior Predictive Performance
  - Techniques like Random Forests and Gradient Boosting Machines offer greater accuracy (De Marchi & Moro, 2023; Jarmulska, 2022).
- Overcoming Limitations of Traditional Models
  - Uncover intricate, nonlinear relationships in fiscal systems.
- Processing Vast and Diverse Data
  - Natural Language Processing enhances predictive power using textual data, reducing false positives and negatives (Chen et al., 2023)

The Common Models of ML

- Random forest; Artificial neural networks; Support vector machines; Extremely randomized tree; Gradient Boosting Machines.

Research Questions

- RQ1: Can machine learning models help better predict fiscal stress in local governments?
- RQ2: What are the top predictors of predicting local fiscal stress?

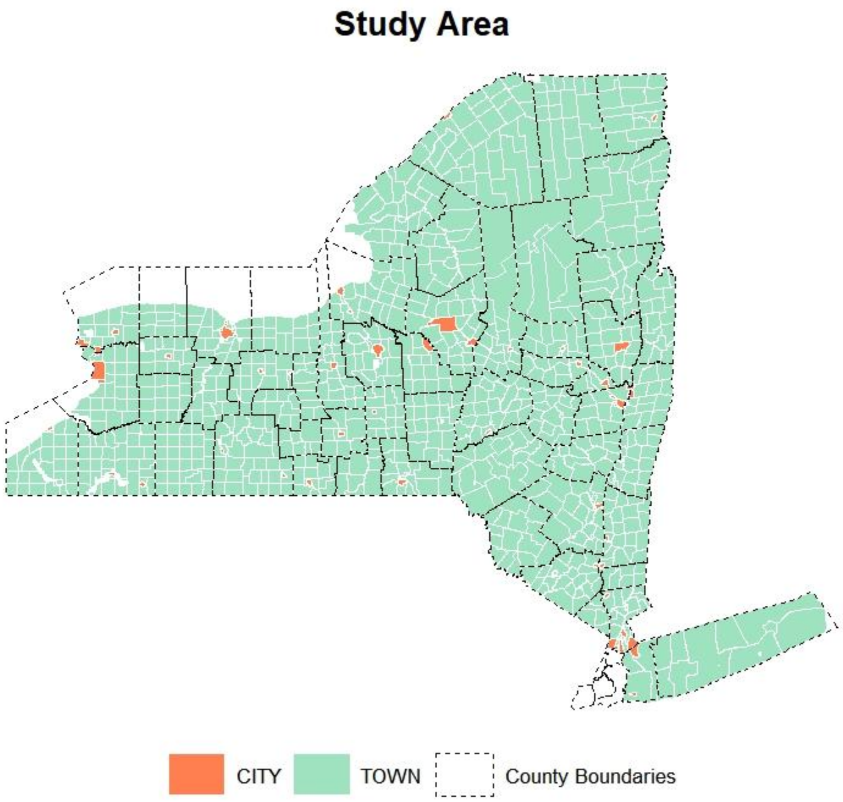
Data Sources

Data Sources Overview: NY State Spending Transparency Website
The New York State Office of the State Comptroller provides a comprehensive overview of state spending. Key data sources include:

1. **State Contracts**: Details on awarded contracts, including vendor information, contract value, and purposes.
2. **Payments**: Information on payments made to vendors, categorized by agency and expenditure type.
3. **Local Government Spending**: Financial data on spending by local governments and public authorities.
4. **Public Authorities**: Data related to financial activities and expenditures of state public authorities.
5. **Procurement Opportunities**: Records of current procurement opportunities and awarded contracts.

Research Area

Summary:
In New York State, cities are **independent** and **self-governing municipalities**, whereas towns are administrative divisions of counties, governing areas that are not part of a city or village. While cities provide their own services and governance, towns may rely on the county for certain functions, and villages within towns often have their own governments. There is no overlap in governance between cities and towns.



There are a total of **61** Cities and a total of **933** towns

CITY and TOWN can cover most of New York State (excluding New York City)

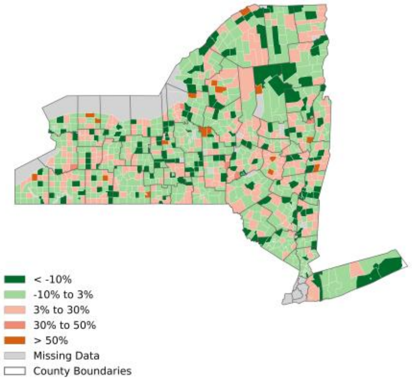
Predicting Outcome Variables: Budget Deficit

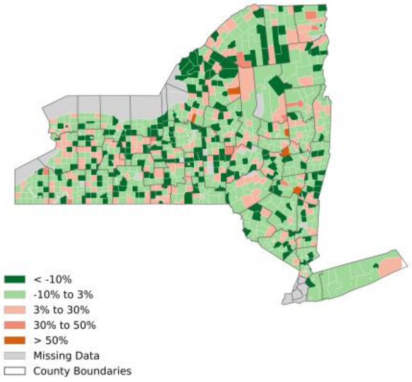
- Limited consensus on a single best measure of fiscal stress for local governments
- Given the focus of this study on early warning and predictive modeling, we selected budget deficit as the primary outcome variable

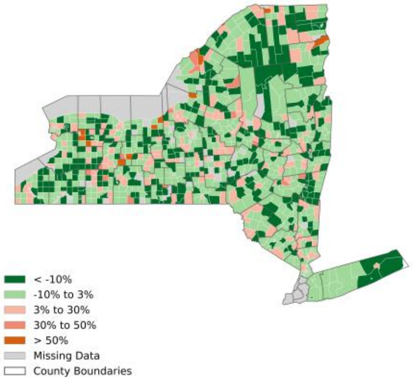
For each municipality *i* in year *t*, the budget deficit ratio BD_{it} is defined as follows:

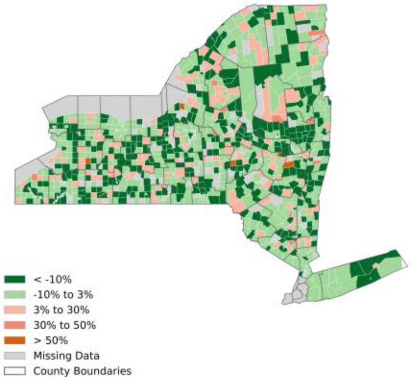
$$Budget\ Deficit\ Ratio(BD)_{i,t} = \frac{Total\ Revenue\ (TR)_{i,t} - Total\ Expenditure\ (TE)_{i,t}}{Total\ Revenue\ _{i,t}} \quad (1)$$

Yearly OP_DEFICIT Visualization (Budget Deficit)

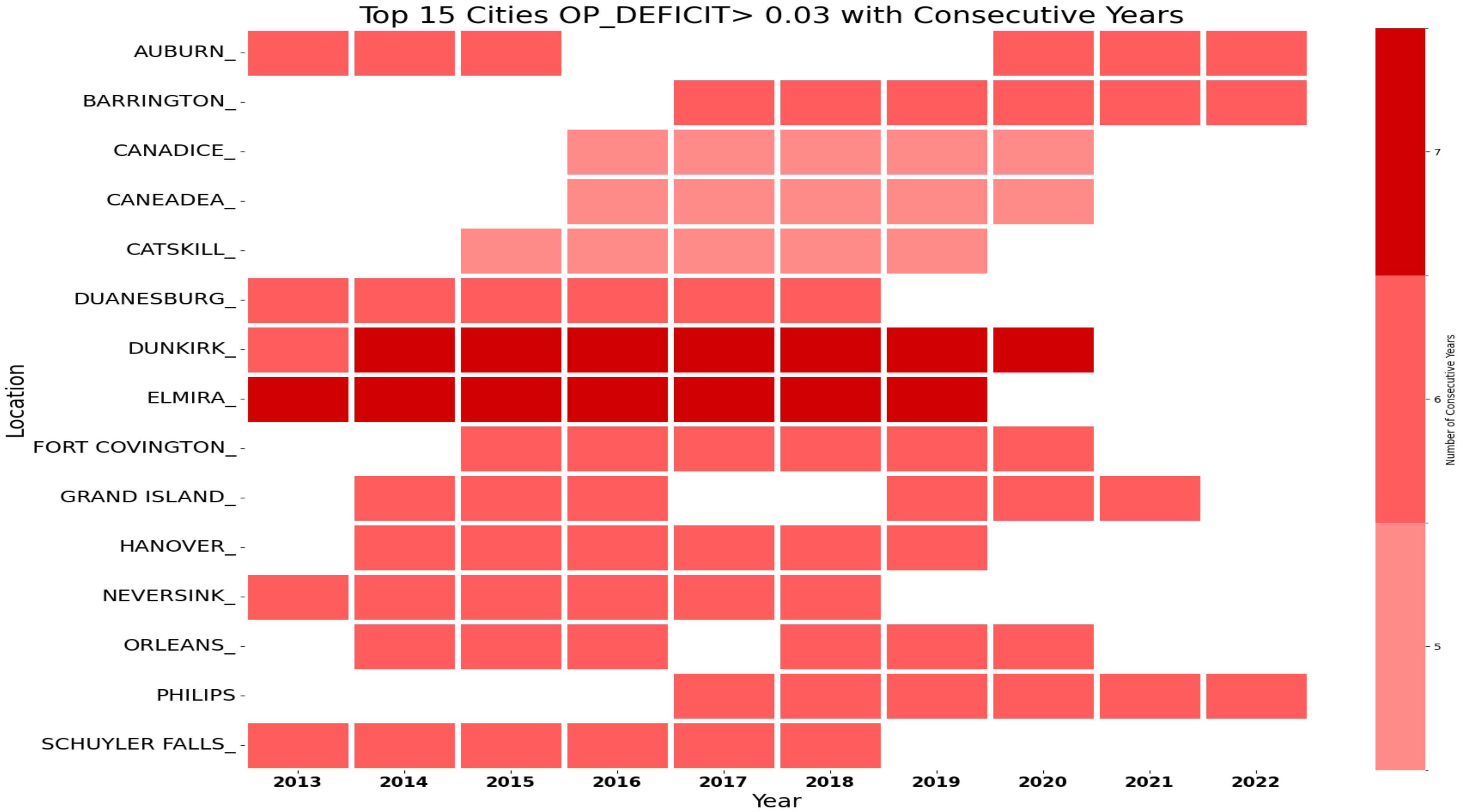








2013 2017 2020 2022


Top 15 Cities OP_DEFICIT> 0.03 with Consecutive Years
AUBURN_
BARRINGTON_
CANADICE_
CANEADEA_
CATSKILL_
DUANESBURG_
DUNKIRK_
ELMIRA_
FORT COVINGTON_
GRAND ISLAND_
HANOVER_
NEVERSINK_
ORLEANS_
PHILIPS
SCHUYLER FALLS_
Location
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Year
7
6
5
Number of Consecutive Years

Data Variables

Financial (21)

TRANSFER_REVENUE	CASH_EXP_RATIO
AID_REVENUE	DEBT_REV_RATIO
SALES_REVENUE	BOND_ISSUE
SALES_TAX_REVENUE	BOND_PAID
PROPERTY_TAX_REVENUE	BOND_ANTICIPATION_ISSUE
PERSONNEL_REV_RATIO	BOND_ANTICIPATION_PAID
ECON_DEV_EXP_RATIO	BOND_ISSUE_EXP_RATIO
DISASTER_EXP_RATIO	BOND_ANT_NOTE_ISSUE_EXP_RATIO
POLICE_EXP_RATIO	BOND_PAID_REV_RATIO
TRANSPORT_EXP_RATIO	BOND_ANT_NOTE_PAID_REV_RATIO
FUND_BALANCE_EXP_RATIO	

Socioeconomic (10)

IND_GINI
Unemployment rate
Service Sector Employment rate
High-Skilled Occupation Employment Rate
Public Sector Employment Rate
Median Household Income
Public Assistance Recipients
Poverty Rate
Uninsured Population Rate
FEMA Disaster Declarations

Demographics (11)

Sex Ratio
Total Population
Adult Population (18+)
Senior Population (65+)
Households with Minors
Average Household Size
High School Graduation Rate
Veteran Population
Disability Rate
Black Population Percentage
Hispanic Population Percentage

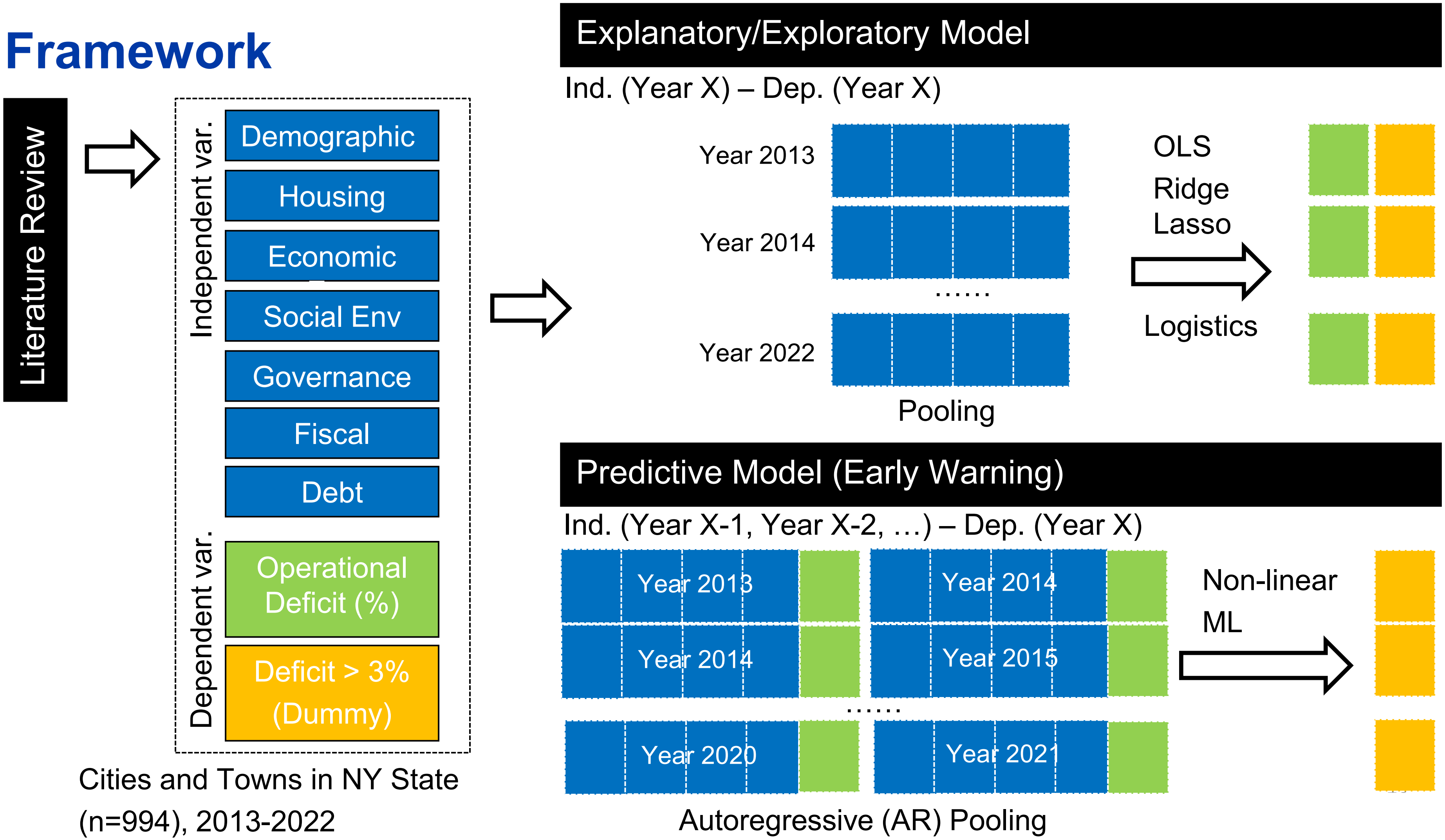
Housing (5)

Vacancy Rate
Renter-Occupied Housing
Median Home Value
GRAPI
SMOCAPI

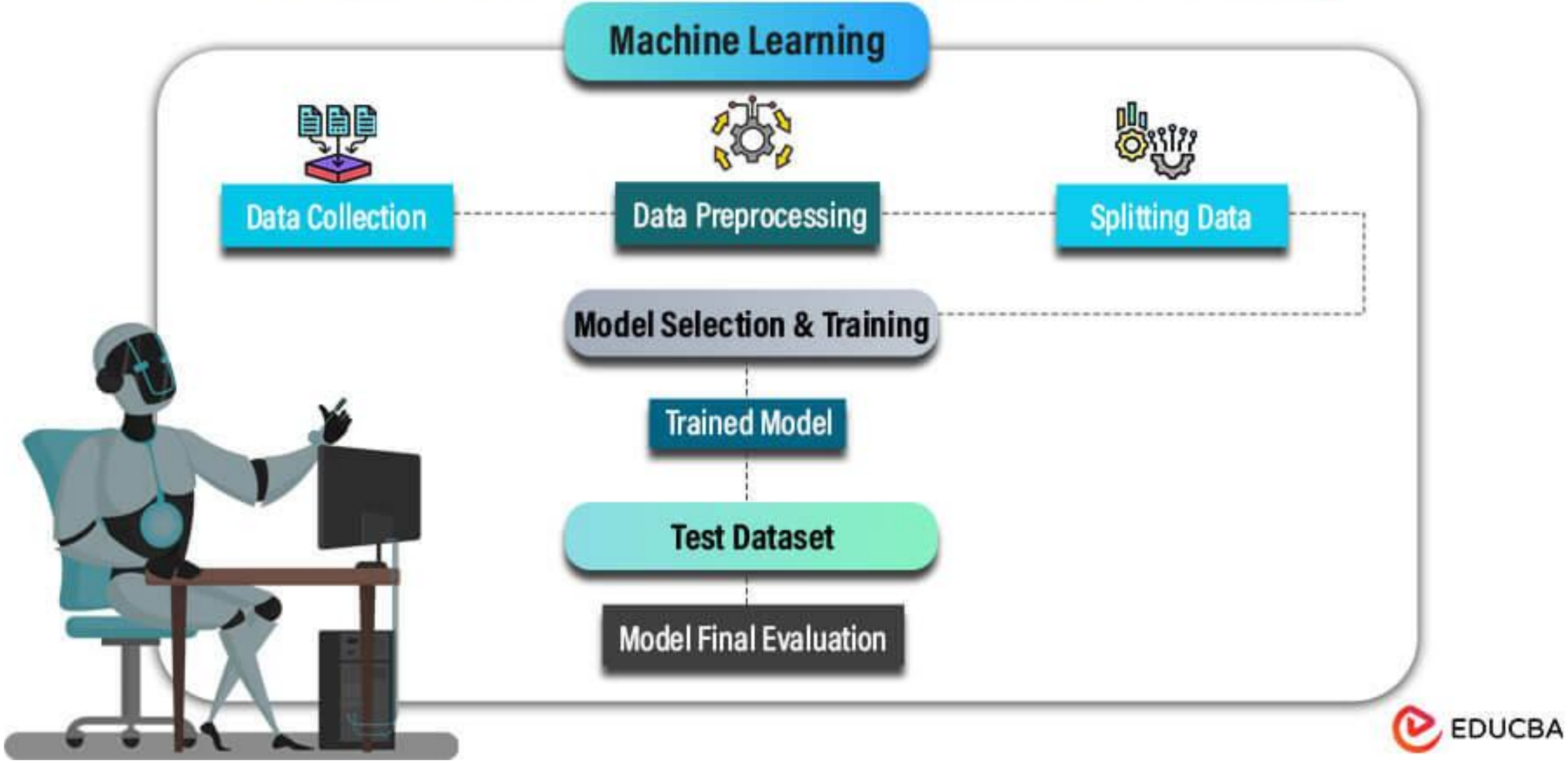
Variable Statistics

	OP_DEFICIT>0.03		OP_DEFICIT<=0.03		Difference_of_Means	p_value
Variable	Mean	SD	Mean	SD		
TOTAL_EXPENDITU	15,055,532.32	55,446,615.07	20,074,013.59	119,199,440.20	-5,018,481.27	0.006(**)
TRANSFER_REVEN	1,877,449.14	10,640,633.41	2,036,590.82	11,543,323.75	-159,141.68	0.54
AID_REVENUE	2,064,067.90	11,304,592.08	2,212,134.71	12,180,507.75	-148,066.81	0.591
SALES_REVENUE	425,014.63	2,877,555.10	1,398,016.96	8,763,634.18	-973,002.33	<0.001(***)
SALES_TAX_REVEN	1,631,493.83	7,549,595.81	1,716,530.65	7,843,426.19	-85,036.82	0.641
PROPERTY_TAX_R	4,884,252.32	17,449,466.69	5,952,607.61	20,072,727.86	-1,068,355.30	0.014(**)
PERSONNEL_EXPE	2,634,979.65	11,928,273.51	2,808,152.90	11,989,595.80	-173,173.25	0.544
ECONOMIC_DEV_E	213,185.92	1,393,502.58	187,186.85	1,267,231.34	25,999.07	0.426
DISASTER_EXPEND	114,573.30	610,497.93	152,049.08	847,802.77	-37,475.77	0.02(**)
POLICE_EXPENDIT	1,305,103.98	6,326,130.56	1,313,000.62	6,413,207.02	-7,896.64	0.959
TRANSPORTATION_	2,097,707.61	5,254,362.48	2,117,189.40	5,595,814.27	-19,481.80	0.879
FUND_BALANCE	3,781,187.97	20,628,656.42	7,143,405.91	26,119,391.91	-3,362,217.94	<0.001(***)
CASH	6,748,111.23	27,309,102.45	9,178,631.50	38,450,830.07	-2,430,520.26	<0.001(***)
DEBT_SERVICE	1,155,733.37	5,466,912.64	1,348,005.29	7,459,563.89	-192,271.92	0.18
OP_DEFICIT	0.157	0.257	-0.086	0.096	0.24	<0.001(***)

Framework


Literature Review
Independent var.
Demographic
Housing
Economic
Social Env
Governance
Fiscal
Debt
Dependent var.
Operational Deficit (%)
Deficit > 3% (Dummy)
Cities and Towns in NY State (n=994), 2013-2022
Explanatory/Exploratory Model
Ind. (Year X) – Dep. (Year X)
Year 2013
Year 2014
……
Year 2022
Pooling
OLS
Ridge
Lasso
Logistics
Predictive Model (Early Warning)
Ind. (Year X-1, Year X-2, …) – Dep. (Year X)
Year 2013
Year 2014
Year 2014
Year 2015
……
Year 2020
Year 2021
Non-linear ML
Autoregressive (AR) Pooling

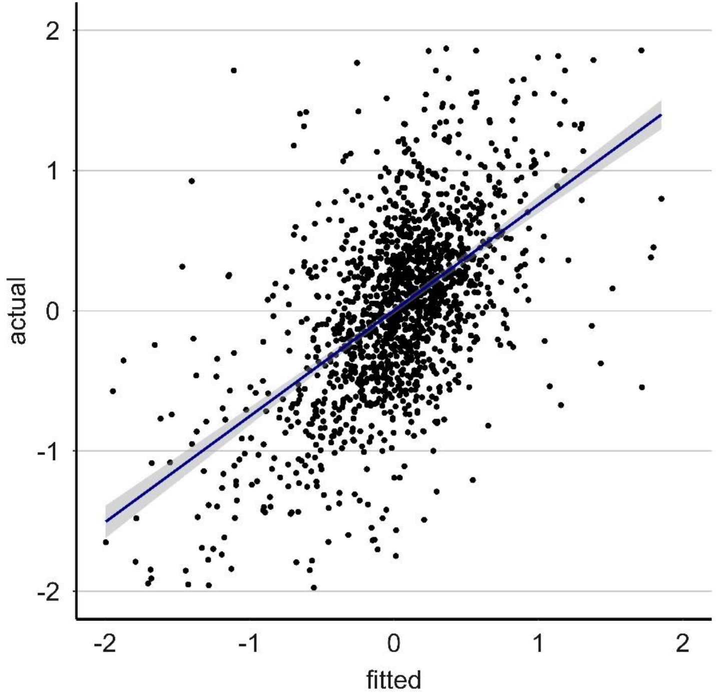
Train and Test in Machine Learning



Model Results

OLS Train Accuracy (R-square): **0.562**

OLS Test Accuracy: **0.542**



Explanatory/Exploratory Model

Operational Deficit (%)

Lasso – Test Accuracy: **0.548** (lambda = 0.02)

Ridge – Test Accuracy: **0.544** (alpha = 0.01)

Model Results

Explanatory/Exploratory Model

	coef	std err	t	P>|t|
PCT_RENTAL	0.0322	0.016	-2.046	0.041
MED_HVALUE	**-0.0546**	0.021	2.55	0.011
PCT_SMOCAPI	0.0387	0.011	-3.537	<0.001
MED_HHINCOME	**-0.0505**	0.024	-2.141	0.032
PCT_HSGRAD	**-0.0353**	0.014	-2.532	0.011
FEMA count	0.0217	0.009	-2.553	0.011
TRANSFER_REV_RATIO	0.0708	0.009	7.763	<0.001
AID_REV_RATIO	**-0.0562**	0.01	-5.403	<0.001
SALE_REV_RATIO	**-0.0962**	0.015	-6.594	<0.001
PERSONNEL_REV_RATIO	0.1289	0.013	10.11	<0.001
POLICE_EXP_RATIO	**-0.117**	0.013	-9.341	<0.001
FUND_BALANCE_EXP_RATIO	**-0.1901**	0.015	-12.297	<0.001
CASH_EXP_RATIO	**-0.1478**	0.015	-9.933	<0.001
BOND_ANTICIPATION_PAID	**-0.0234**	0.009	-2.59	0.01
BOND_ISSUE_EXP_RATIO	**-0.3625**	0.015	-23.934	<0.001
BOND_ANT_NOTE_ISSUE_EXP_RATIO	0.3199	0.01	33.56	<0.001
BOND_PAID_REV_RATIO	0.1367	0.013	10.544	<0.001
BOND_ANT_NOTE_PAID_REV_RATIO	**-0.1447**	0.012	-11.791	<0.001

No. Observations:	6474
F-statistic:	183.1
Log-Likelihood:	-6516.3

Operational Deficit (%)

Model Results

Deficit > 3%
(Dummy)

Explanatory/Exploratory Model

Train Accuracy (Pseudo R-square): **0.724**

Test Accuracy: **0.723**

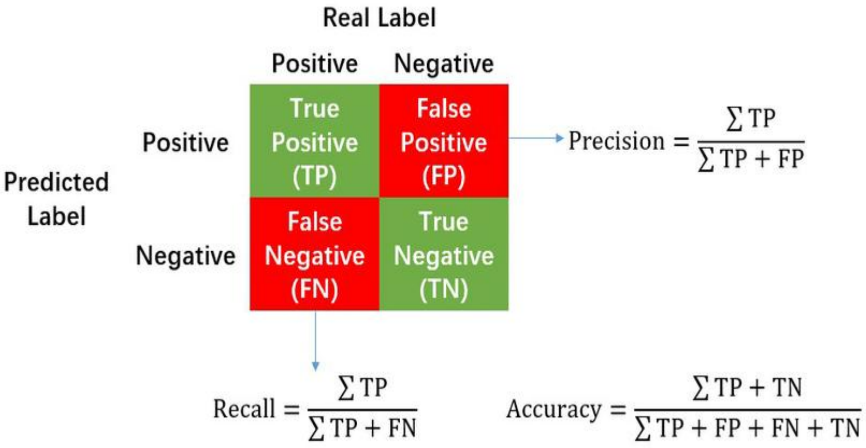
	coef	std err	t	P>|t|
PCT_DISABILITY	0.0854	0.04	-2.132	0.033
TRANSFER_REV_RATIO	0.2055	0.03	6.826	0
SALE_REV_RATIO	-0.2898	0.055	-5.272	0
SALES_TAX_REV_RATIO	-0.0965	0.043	-2.256	0.024
PERSONNEL_REV_RATIO	0.2751	0.042	6.621	0
POLICE_EXP_RATIO	-0.1582	0.041	-3.867	0
TRANSPORT_EXP_RATIO	0.1653	0.049	3.377	0.001
FUND_BALANCE_EXP_RATIO	-0.392	0.056	-6.971	0
DEBT_REV_RATIO	0.0968	0.046	2.124	0.034
BOND_ANTICIPATION_PAID	-0.1524	0.058	-2.639	0.008
BOND_ISSUE_EXP_RATIO	0.1184	0.065	1.826	0.068
BOND_ANT_NOTE_ISSUE_EXP_RATIO	0.9888	0.061	16.175	0
BOND_ANT_NOTE_PAID_REV_RATIO	-0.1949	0.057	-3.444	0.001
No. Observations:	6474			
Log-Likelihood:	-3959.8			

Robustness Check:

Test Accuracy when the deficit threshold is

0%: 0.681 2%: 0.704 4%: 0.739

6%: 0.762 8%: 0.792 10%: 0.813



Model Results

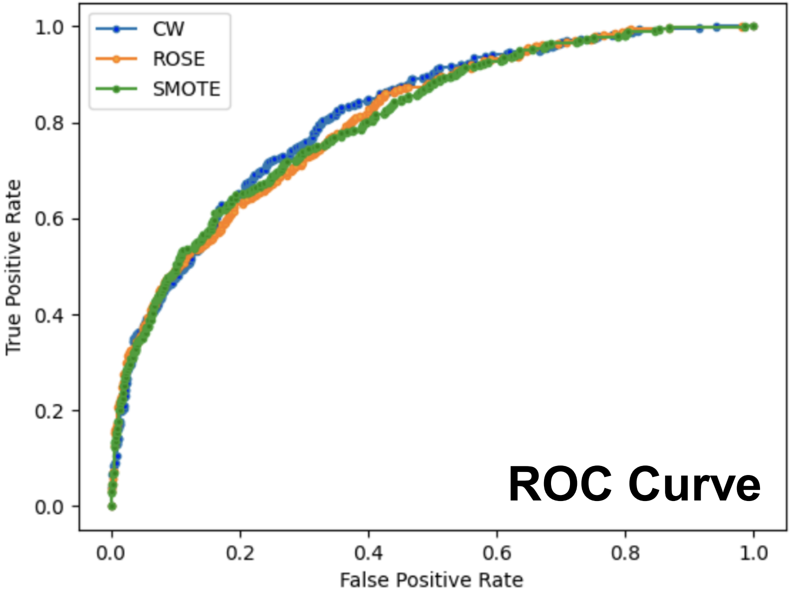
Deficit > 3% (Dummy)

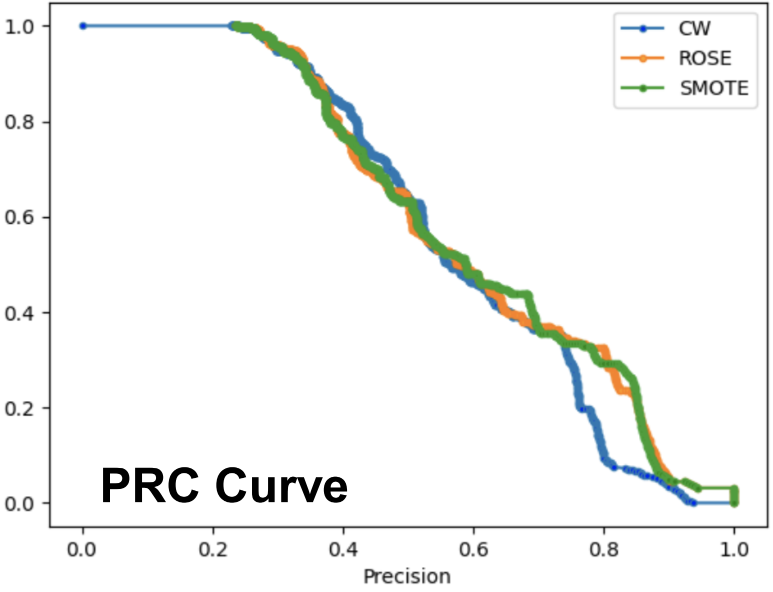
Explanatory/Exploratory Model

Datasets	PRC -AUC	ROC -AUC	Accuracy
CW	0.590	0.804	0.737
ROSE	**0.631**	**0.819**	0.799
SMOTE	**0.636**	**0.818**	**0.817**

SMOTE resampling has the best model accuracy and robustness, compared to other resampling techniques

Note: Average performance metrics based on resampling for 1000 times

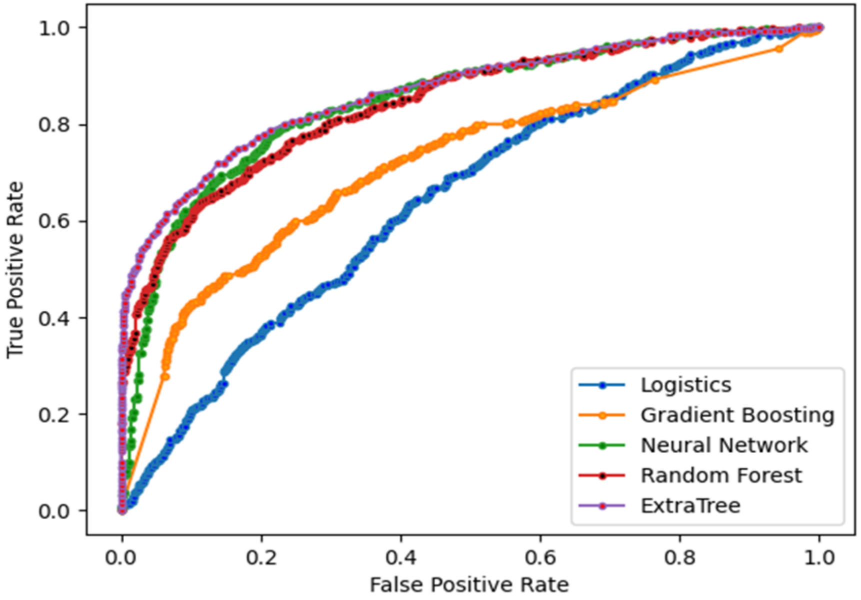




Results

Predictive Model (Early Warning)

ML algorithms	PRC	ROC	Accuracy
Logistics	0.111	0.642	0.665
Gradient Boosting	0.283	0.714	0.704
Neural Network	0.403	0.846	0.788
Random Forest	**0.448**	**0.842**	**0.794**
Extremely Randomized Trees	**0.491**	**0.865**	**0.825**



Non-linear supervised learning algorithms produced much better prediction accuracy and precision than conventional linear classifier (Logistics)

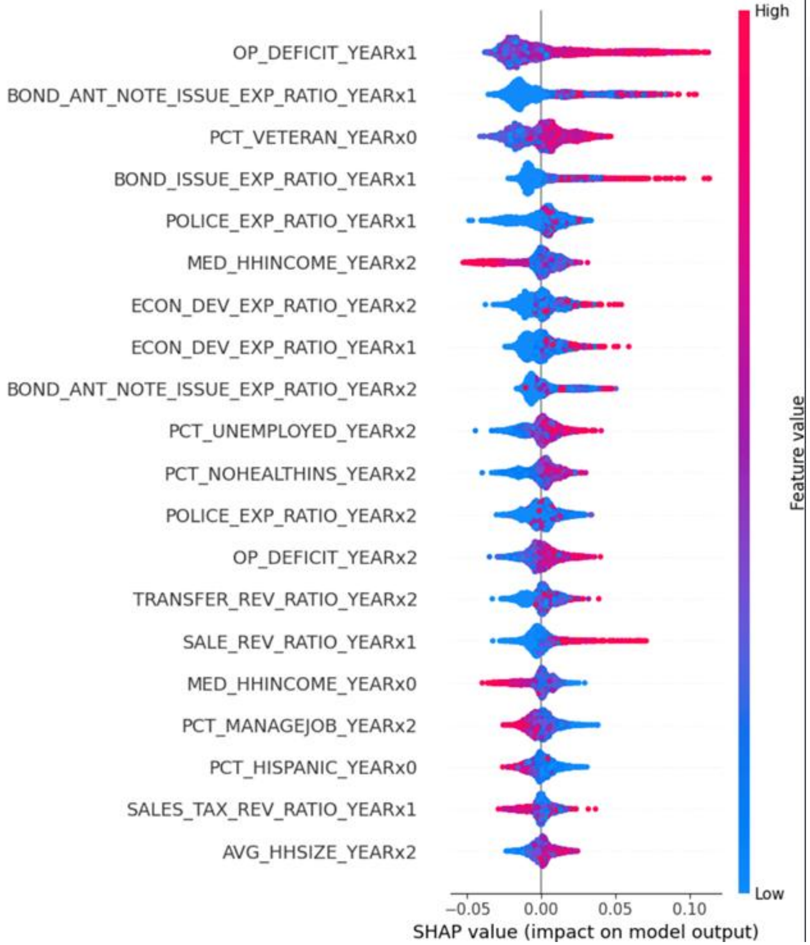
Ensemble tree-based methods had the best performance among popular ML algorithms.

ROC Curve

Deficit > 3%
(Dummy)

Model Results - Feature Importance

Predictive Model (Early Warning)



Deficit, **bond issuance**, and **key expenditures of previous years** contributed most to predict current year deficit

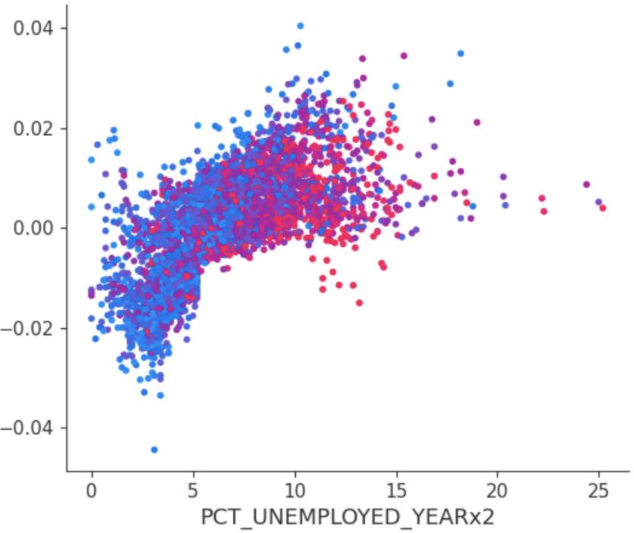
The socioeconomic status of local communities (median household income) is highly linked with the likelihood of deficit status.

Deficit > 3%
(Dummy)

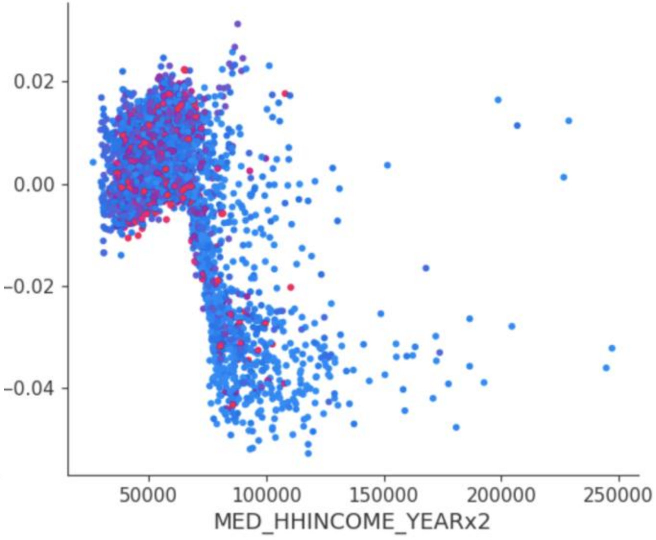
Model Results - Dependence

Predictive Model (Early Warning)

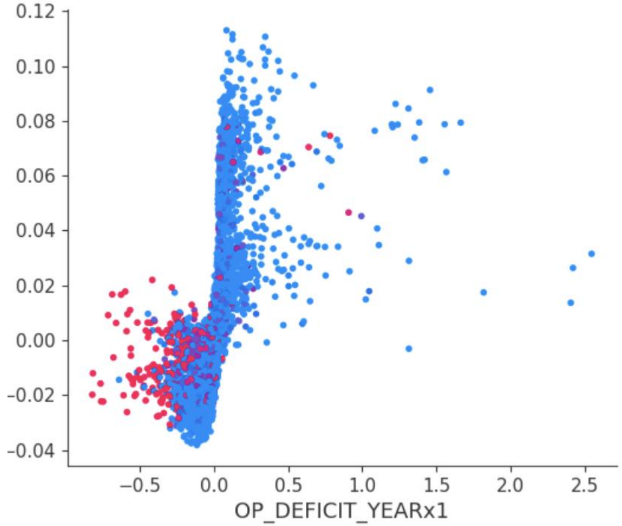
Unemployment Rate-2 (positive)



Median Household Income Year-2 (negative)



Deficit % Year-1 (positive)



Conclusion

- Machine learning models significantly outperformed traditional linear classifiers (e.g., logistic regression) in predicting local fiscal stress.
  - Non-linear algorithms (e.g., random forests, extra trees) achieved higher accuracy and precision.

- **Deficit**, **bond issuance**, and **key expenditures of previous years** contributed most to predict current year deficit

- Data gaps remain, especially in capturing local governance structures, political dynamics, and institutional factors that may influence fiscal outcomes.

Thank You!

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Four Machine Learning Algorithms in Local Fiscal Stress Prediction

Algorithm	Type	Key Characteristics	Advantages
Random Forests	Ensemble (Bagging)	Aggregates multiple decision trees using bootstrap sampling	Reduces variance, handles overfitting, interpretable feature importance
Extremely Randomized Trees	Ensemble (Bagging)	Similar to Random Forests but with random split thresholds	Faster training, further variance reduction
Gradient Boosting Machines	Ensemble (Boosting)	Sequentially adds trees to correct previous errors	High predictive accuracy, effective for complex nonlinear patterns
Artificial Neural Networks	Deep Learning	Multi-layer networks that learn through backpropagation	Captures complex nonlinear relationships, adaptable to high-dimensional data

Variable Transformation

Independent Variables:

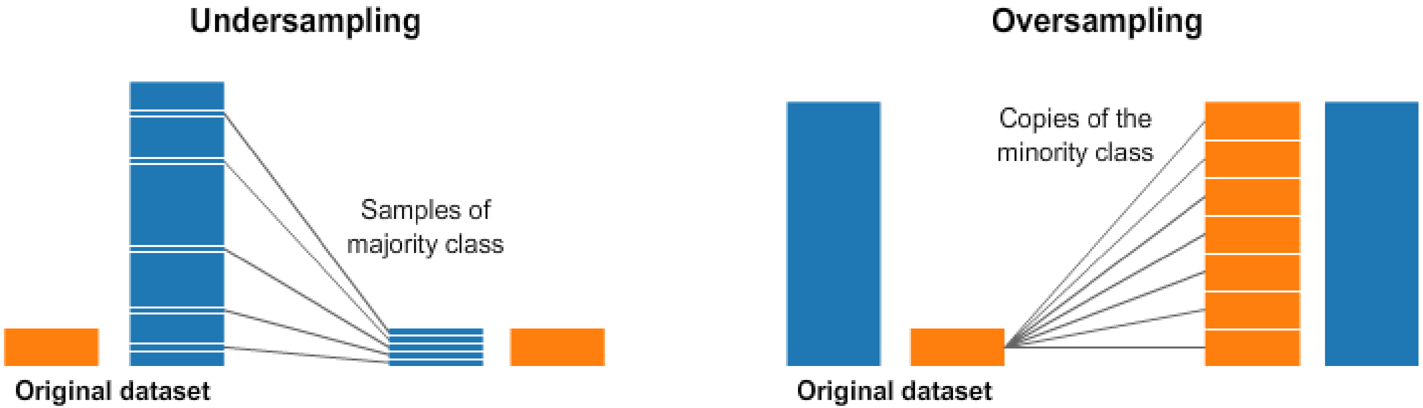
- impute missing values by column mean
- standardize

Dependent Variable (Deficit %):

- Yeo-Johnson transformation (power transformation)

$$\psi(\lambda, y) = \begin{cases} ((y+1)^{\lambda} - 1)/\lambda & \text{if } \lambda \neq 0, y \geq 0 \\ \log(y+1) & \text{if } \lambda = 0, y \geq 0 \\ -[(-y+1)^{2-\lambda} - 1)]/(2-\lambda) & \text{if } \lambda \neq 2, y < 0 \\ -\log(-y+1) & \text{if } \lambda = 2, y < 0 \end{cases}$$

Resampling for Imbalanced Datasets



20%
Deficit > 3%

80%
Deficit < 3%

1. Class Weights (CW)

Assign larger weights to minority data points

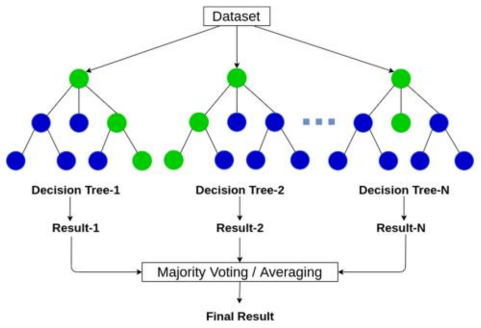
2. Random Over-sampling Examples (ROSE)

Up-sample data points repetitively from the minority group

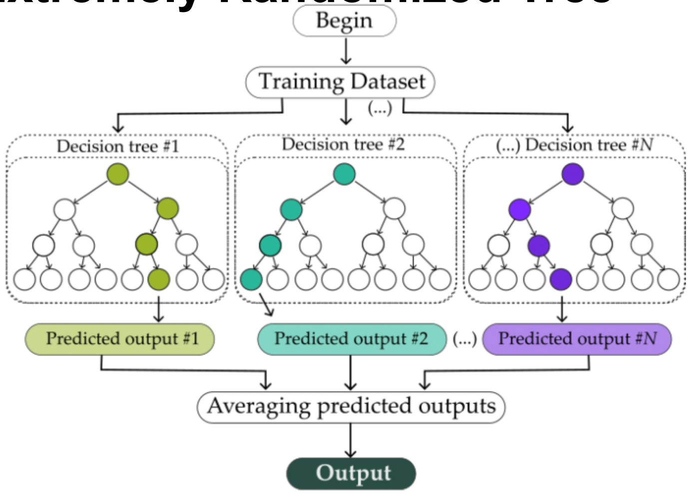
3. Synthetic Minority Over-sampling Technique (SMOTE)

Generate synthetic data points from the minority group

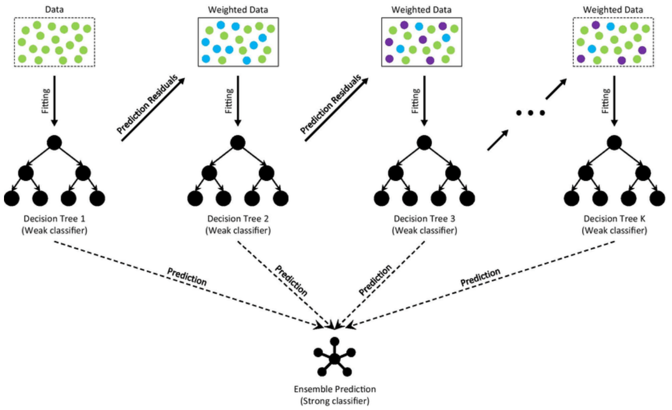
Random Forest



Extremely Randomized Tree



Gradient Boosting Machines



Architecture of Artificial Neural Network