RUTGERS
THE STATE UNIVERSITY OF NEW JERSEY

World Bank
December 2, 2020

SHAPING THE FUTURE IN BUSINESS MEASUREMENT AND ASSURANCE: EMBRACING TECHNOLOGY AND CHANGE

Creating a Digital Strategy

Outline

- Introduction
  - The CarLab
- Some of our projects
  - GASB –PIR
  - Exogenous Data
  - PIOB – what is public interest?
  - Machine Learning for accounting estimates
  - Big data analytics
  - Cooperation with the Volcker Alliance
  - Continuous assurance of medication procurement of a state
  - NYC cleanliness with Tweet text mining
  - Continuous pandemic monitoring

CarLab

The CarLab

INTRODUCTION

All academic Accounting programs around the world are ranked annually by BYU. For many years now, the Accounting Information Systems (AIS) group at RBS has led the world in the application of information technology to the audit profession. We are very proud to announce that the just-released BYU rankings for 2019 confirm again the continued success of Rutgers Business School in both AIS and audit research:

Main Ranking for Accounting Information Systems (all methods) 2019

Top of Form

University	Last 6 Years	Last 12 Years	All Years
Rutgers, The State University of New Jersey	1	1	1

Main Ranking for Auditing (all methods) 2019

University	Last 6 Years	Last 12 Years	All Years
Rutgers, The State University of New Jersey	7	9	11


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Rutgers
Business
School
EXIT

Updating Dashboard with document links

http://raw.rutgers.edu/CAR%20Lab%20Directory/Sign-in.html

PASSWORD: RARC777


abc

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GASB Post-Implementation Review Project

Ben Yoon

Huaxia Li

Kevin Moffitt

Rutgers CarLab

July 2020

Project Objectives

- This project will build a dynamic information system that

  1) automatically captures the CAFRs from different governmental entities,

  2) parses relevant items from the CAFRs, and

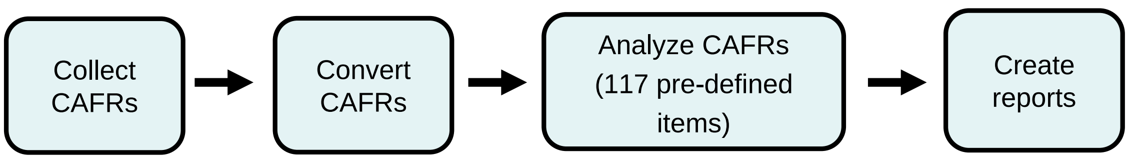
  3) converts them into a structured data

- The structured data be easily used by the GASB to perform the post-implementation review (PIR) of the new GASB pension standards.

  * In 2012, the GASB announced new pension standards (No. 67 and 68).

4 Steps of This Project

- This project consists of 4 steps.



- Rutgers has conducted initial pilot tests.
  - Step1: Collecting 36,676 CAFRs from 3 repositories
  - Step2: Converting PDF documents
  - Step3: Extracting 8 items from the CAFRs
  - Step4: Report with Excel format

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Exogenous data analytics for Auditing

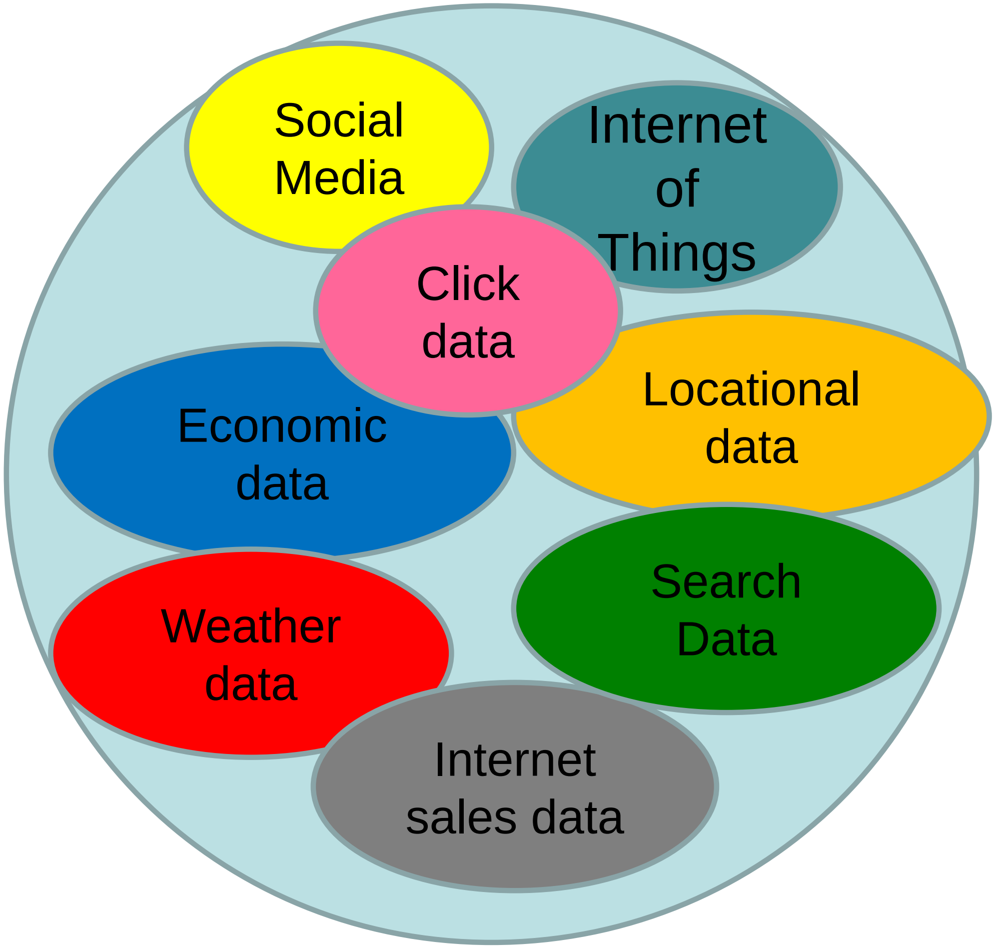
Miklos A. Vasarhelyi
Helen Brown Liburd

Rutgers Business School

Some sources

- Amazon sales
- Google searches
- Apps used
- Calls made
- GPS or JEEP location
- Sites accessed
- Car license plates photographed
- Pictures of parking lots
- Face recognition pictures
- Site clickpaths

Exogenous Data



ED may be of easier access

ED is likely less tamperable

ED relationships will be stochastic

ED is a form of confirmation

ED may complement many current procedures

ED may create many new procedures

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IFAC / PIOB project

Kevin Moffitt

Ben Yoon

Hiaxia Li

Rutgers/ PIOB / IFAC Project

- The Public Interest Oversight Board (*PIOB*) is the global independent oversight body that seeks to improve the quality and public interest focus of the international audit and assurance, and ethics standards formulated by the Standard Setting Boards supported by the International Federation of Accountants (IFAC).
- The Rutgers team will automatically identify public interest regarding auditing from investor, regulator, and professional accounting websites.

Problem: Automatically identify public interest from investors, regulators, etc…

- Collected and cleaned 7159 documents from 5/40 identified organizations
  - ESMA - 4145
  - IOSCO - 1164
  - SIFMA - 959
  - THEIA - 731
  - ICGN – 160
- Searched 30 topics identified by PIOB

audit deficiencies	conflict of interest	fee dependency	objectivity
audit quality	critical mindset	fraud	professional skepticism
auditor independence	ethical behavior	going concern	…and more…

Example Sentences Automatically Identified from Websites

Audit Quality	www.IOSCO.org 2018 – "this may provide an effective safeguard that a decision is not unduly influenced by a low audit fee in circumstances where audit quality may be compromised."
Auditor Independence	www.ICGN.org 2018– "so, as you can see, while things have changed since the passage of the sarbanes-oxley act, it appears that new threats to auditor independence have emerged, and that others have reappeared."
Going Concern	www.ESMA.Europa.eu 2019 – "accordingly, the fair value of the land should be determined based on the current use of the land in view of the going concern principle."
Fraud	www.THEIA.org 2019 – "would it be possible to devise a 'reasonable person' test in assessing the auditors work in relation to fraud detection?"
Professional Skepticism	www.THEIA.org 2019 – "annually it should assert why it believes the auditor has been challenging and exercised professional skepticism."

Machine Learning Improves Accounting Estimates

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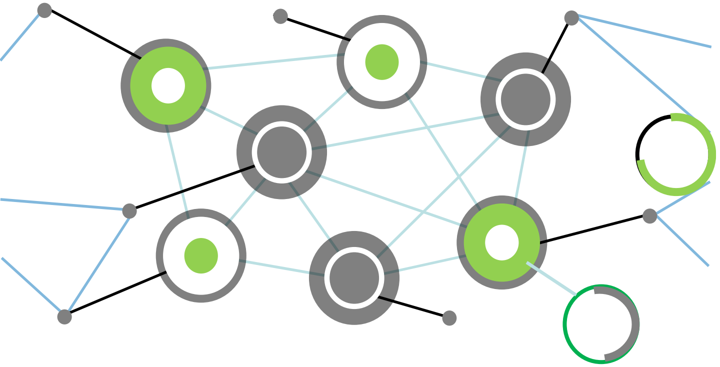
Baruch Lev[2]
Xuan Peng[3]
Ting Sun[4]
Miklos A. Vasarhelyi[5]

[1]Southwestern University of Finance and Economics; and Rutgers, the State University of New Jersey
[2]Stern School of Business, New York University
[3]Southwestern University of Finance and Economics; and Rutgers, the State University of New Jersey
[4]The College of New Jersey
[5]Rutgers, the State University of New Jersey

Accounting Estimates

- Accounting estimates are highly uncertain and are sometimes manipulated.
- Accounting estimates are difficult to audit and impossible for investors to evaluate.
- Accounting estimates are ubiquitous in financial reporting.
  - Example: account receivables, insurance loss reserves, revenues from contracts, and pension and warranty expenses.
- Researchers have made several proposals:
  - Financial statements disclose which accounts are subject to extreme uncertainty (Christensen et al. 2012).
  - Firms report ex-post realization of critical estimates (e.g., Lundholm 1999).
  - Managers restate earnings in case of large deviations (Lev et al. 2008).

Machine Learning Algorithms



- Linear Regression
- Random Forest
- Gradient Boosting Machine (Gradient Tree Boosting)
- Artificial Neural Networks

Main Results Summarized

Table 5 Cross-validation results

Business line	Training/Validation Sample	Obs	Managers' estimates		Machine learning without manager estimates				Machine learning with manager estimates			
			MAE	RMSE	MAE	RMSE	Accuracy edge (MAE)	Accuracy edge (RMSE)	MAE	RMSE	Accuracy edge (MAE)	Accuracy edge (RMSE)
					Random forest				**Random forest**			
Private Passenger Auto Liability	1996-2005	5,949	9,461	37,494	8,213	34,687	13%	7%	7,758	36,071	18%	4%
	1996-2006	6,298	9,793	38,266	7,848	34,547	20%	10%	7,220	30,305	26%	21%
	1996-2007	6,602	9,575	37,940	7,869	35,047	18%	8%	6,902	30,220	28%	20%
					Random forest				**Random forest**			
Commercial Auto Liability	1996-2005	5,383	4,209	18,562	3,565	14,051	15%	24%	3,446	13,555	18%	27%
	1996-2006	5,661	4,155	18,375	3,520	13,881	15%	24%	3,266	13,583	21%	26%
	1996-2007	5,957	4,338	19,175	3,575	13,671	18%	29%	3,322	13,121	23%	32%
					Random forest				**Random forest**			
Workers' Compensation	1996-2005	4,183	11,547	43,652	7,518	29,418	35%	33%	7,144	28,629	38%	34%
	1996-2006	4,398	12,360	44,187	7,434	29,387	40%	33%	6,988	26,888	43%	39%
	1996-2007	4,645	13,214	47,541	7,298	29,468	45%	38%	6,861	26,574	48%	44%
					Random forest				**Random forest**			
Commercial Multi-Peril	1996-2005	5,235	5,737	27,615	5,103	22,060	11%	20%	4,854	22,062	15%	20%
	1996-2006	5,457	5,871	27,931	5,151	23,404	12%	16%	4,968	22,308	15%	20%
	1996-2007	5,846	6,017	28,349	4,963	22,556	18%	20%	4,534	21,265	25%	25%
					Linear regression				**Linear regression**			
Homeowner/Farmowner	1996-2005	6,121	3,905	16,789	5,674	22,069	-45%	-31%	4,402	16,359	-13%	3%
	1996-2006	6,544	3,878	16,611	5,687	21,070	-47%	-27%	4,203	16,201	-8%	2%
	1996-2007	6,946	3,962	16,826	5,548	21,269	-40%	-26%	4,321	16,674	-9%	1%

Concluding Remarks

- There is an urgent need to enhance the quality of accounting estimates and auditors' ability to independently evaluate the reliability of these estimates.

- Machine learning can generate accounting estimates useful for auditors to evaluate managers' estimates, and for managers to generate original estimates.

- These finding should be of value for consideration of the value of machine learning models to standard setters.

- More research is needed to generalize the application of machine learning in other accounting settings.

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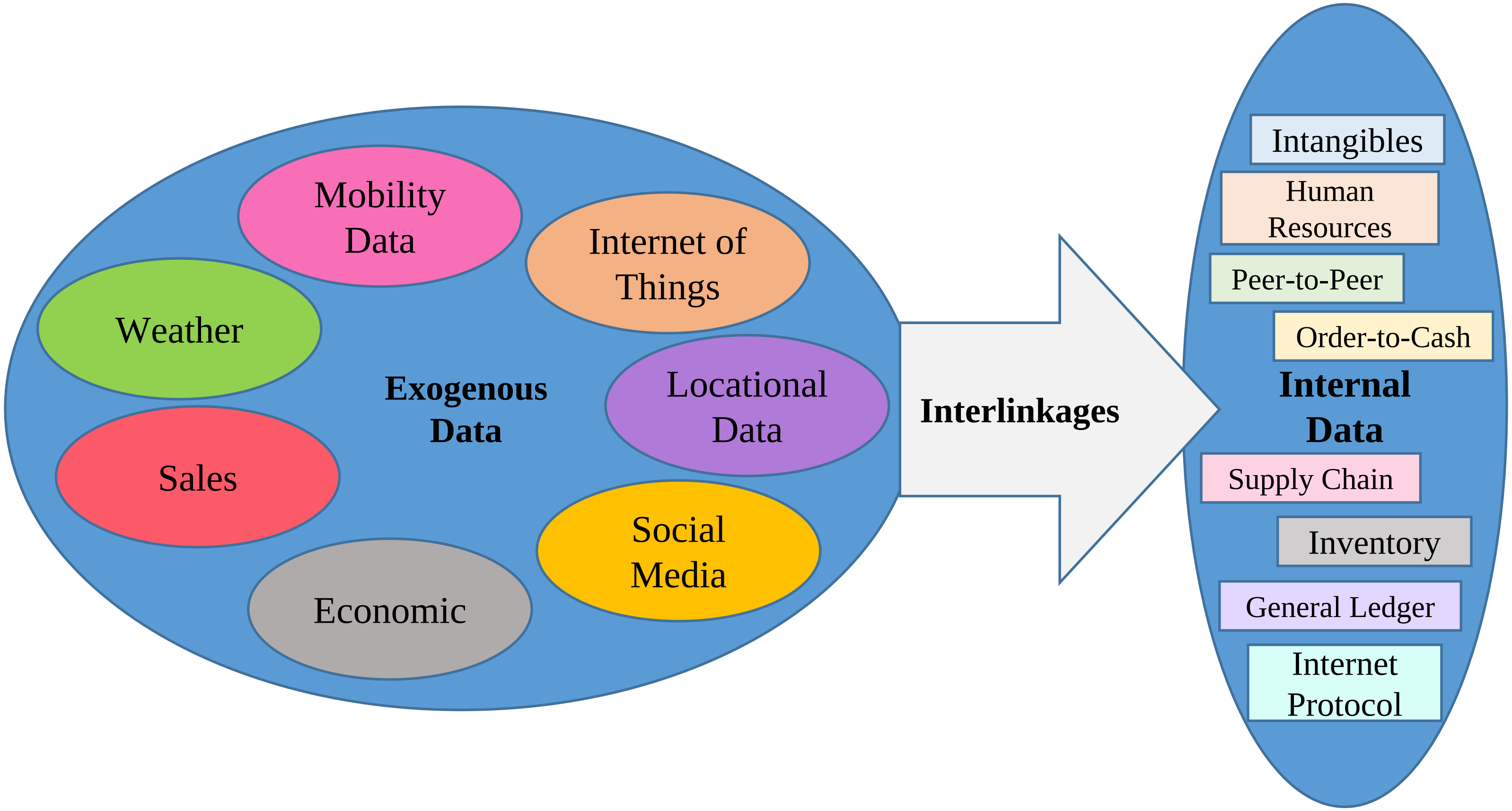
Big data and algorithmic trading against periodic and tangible asset reporting: the need for U-XBRL

Dr. Miklos A. Vasarhelyi
KPMG Distinguished Professor Rutgers Business School - Newark & New Brunswick
Director, Rutgers Accounting Research Center & Continuous Auditing & Reporting Lab

Duo (Selina) Pei
PhD Student Rutgers Business School - Newark & New Brunswick

Some other phenomena observed



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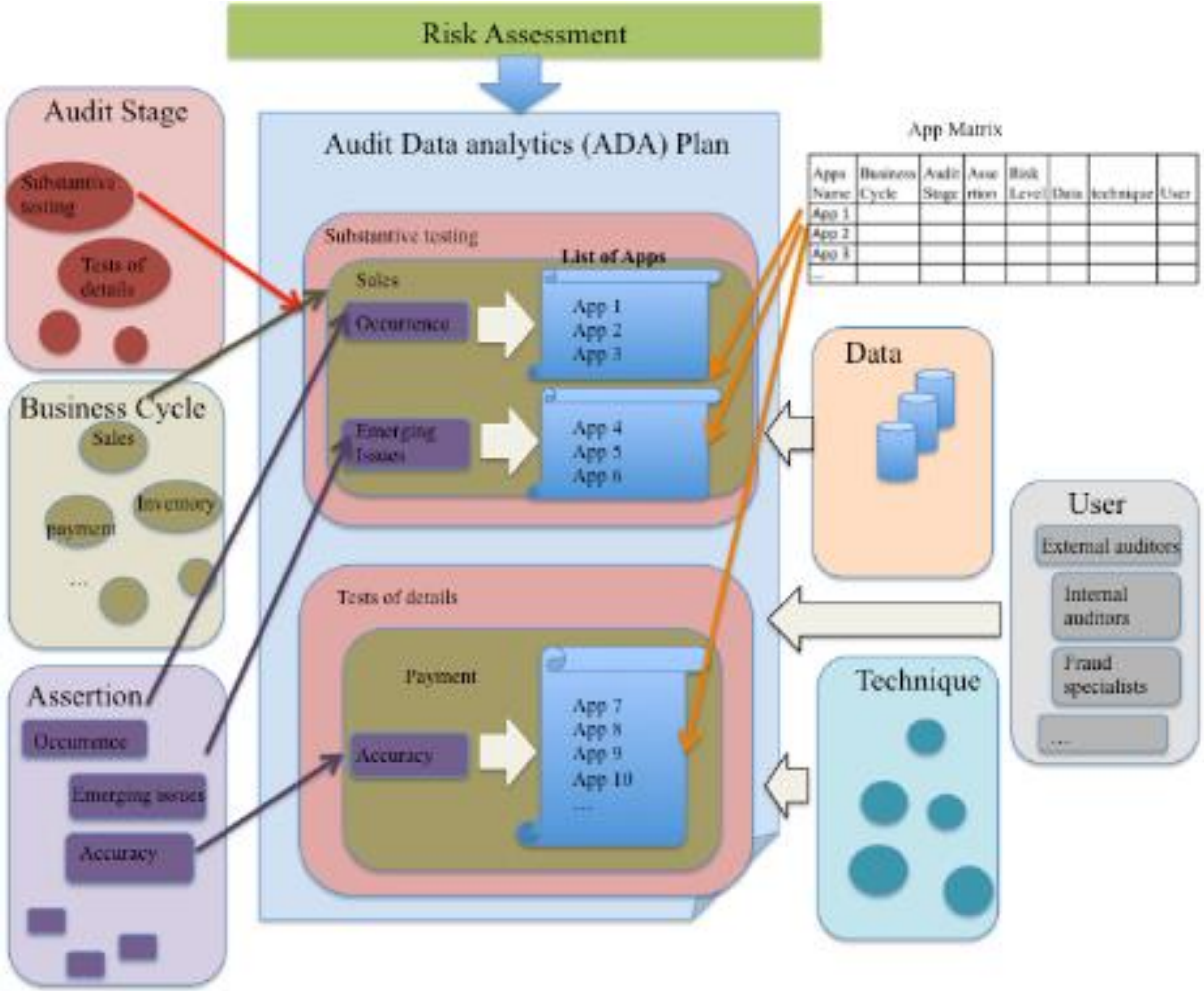
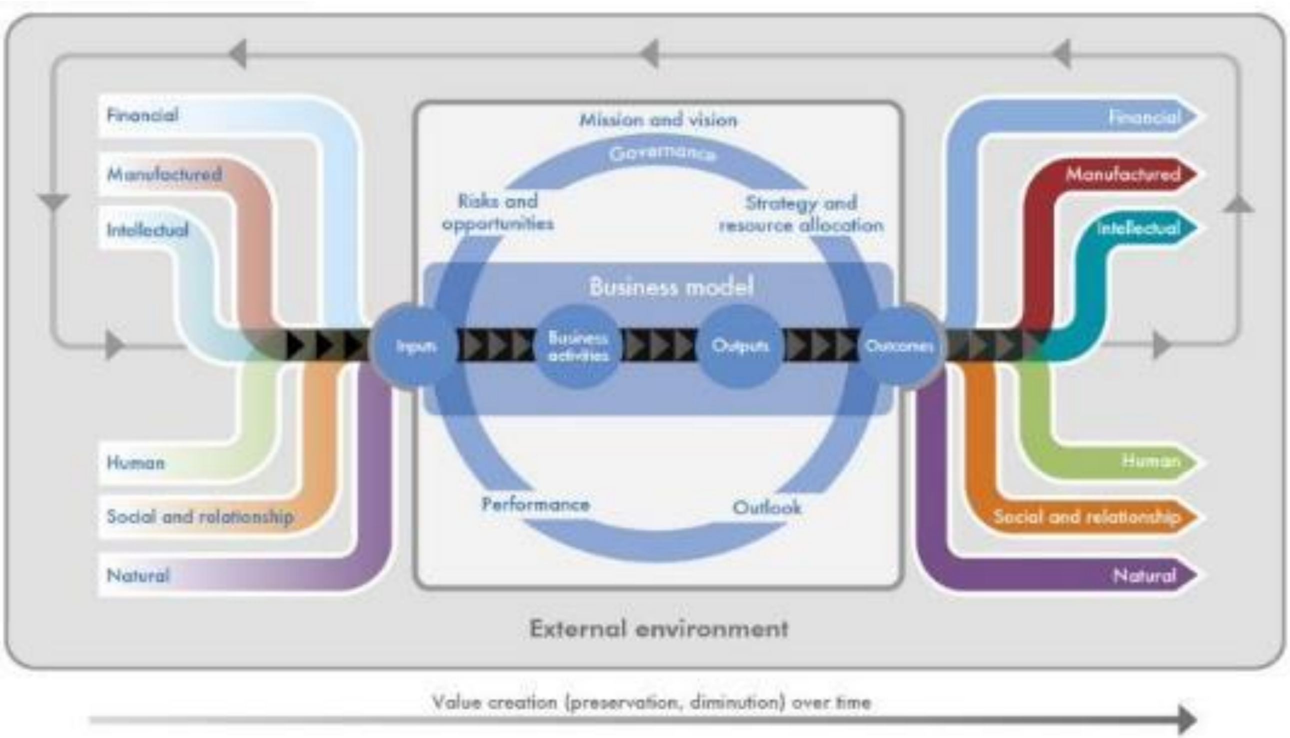
We need a reporting schema that also integrates well with current advances in auditing



Apps Name	Business Cycle	Audit Stage	Assertion	Risk Level	Data	technique	User
App 1							
App 2							
App 3							
...							

So what kind of information may be missing?

- SASB metrics
  - Intellectual property and data privacy (Industry-specific)
  - Integrity and recruitment/retention programs (Overall)
- "The relationships between [an organization's] various operating and functional units and the capitals that the organization uses or affects" in the International Integrated Reporting Council Framework (2013)



APPLICATIONS OF DATA ANALYTICS: VISUALIZATION AND CLUSTER ANALYSIS OF GOVERNMENTAL DATA – TWO CASE STUDIES

ESSAY 2: COOPERATION WITH THE VOLCKER ALLIANCE

OBJECTIVES

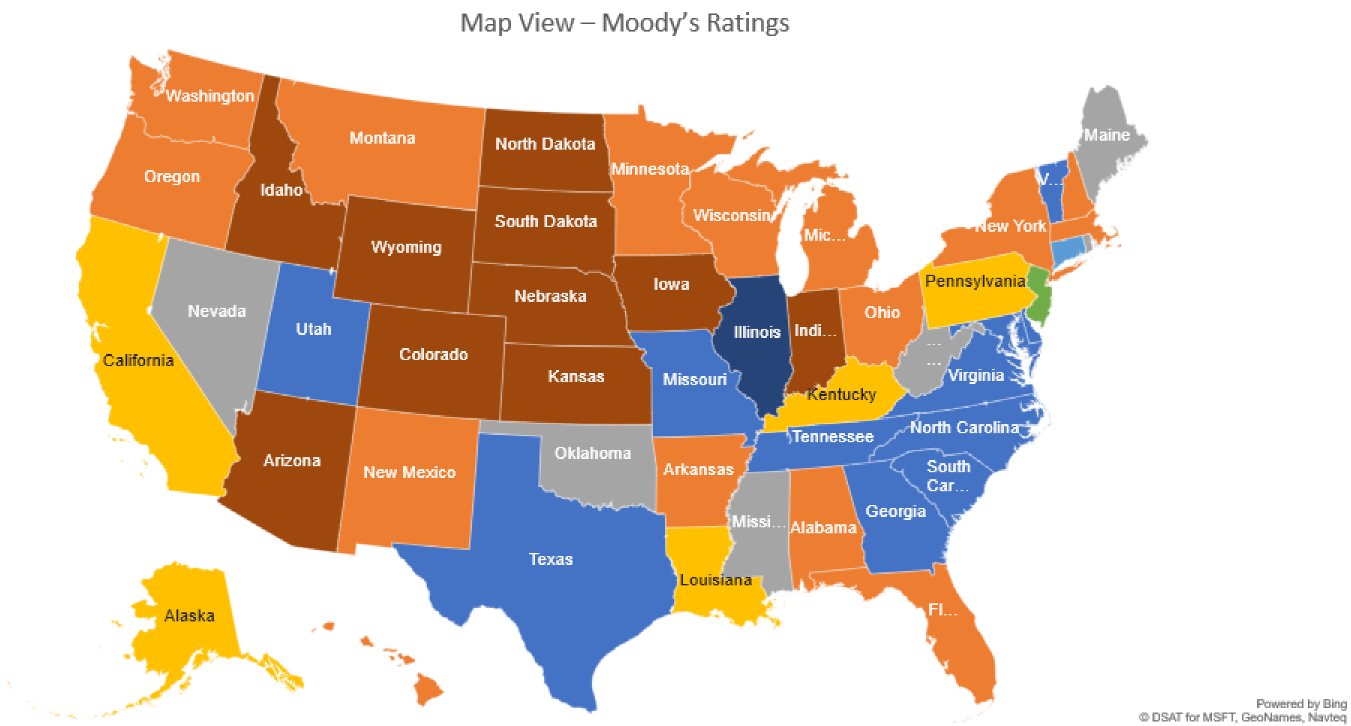
- Since data analytics is one way to explore the data and to help uncover hidden relationships
  - In these case studies we plan to explore the literature for the use of emerging data mining techniques in auditing
    - ✓ In particular, cluster analysis & visualization techniques as supportive tools to gain more insights into data.
- Conduct two case studies:

  1) Rutgers AICPA Data Analytics Research Initiative (RADAR): A Case Study.
     - ✓ Facilitate the integration of different data analytics tools and techniques into the audit process.
  2) Visualization and Clustering Analytics of U.S. states' on budgeting.
     - ✓ Information on U.S. States.

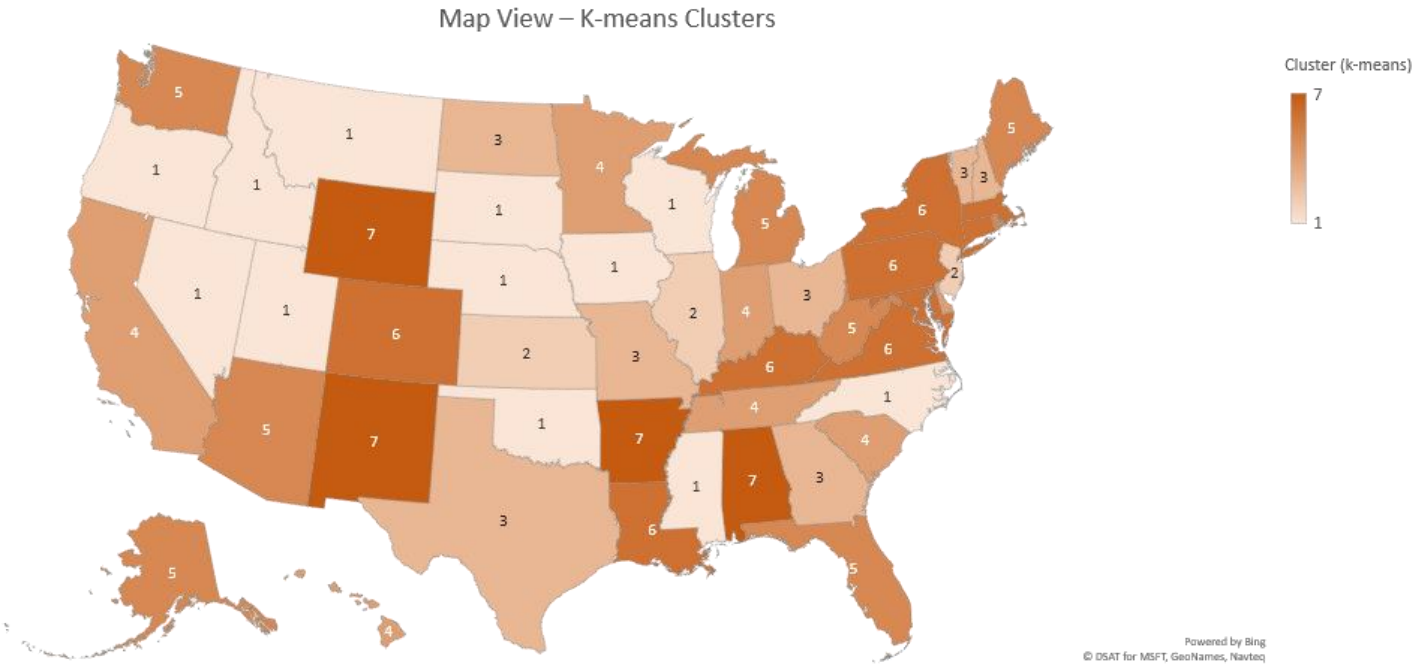
CONTRIBUTION

- We show how visualization and data clustering techniques could be used on governmental data and to help gain more information about financial statements & budgeting.

CONT'D: Moody's Ratings



CONT'D: Clustering Results



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Continuous Monitoring and Audit Methodology for Medication Procurement

Wenru Wang – Rutgers University

Miklos A. Vasarhelyi – Rutgers University

Overview

- Prefeitura de Rio de Janeiro. 30,000+ Medication procurement data, 2017 – 2019.
- Continuous monitoring and audit system for exception and anomaly detections.

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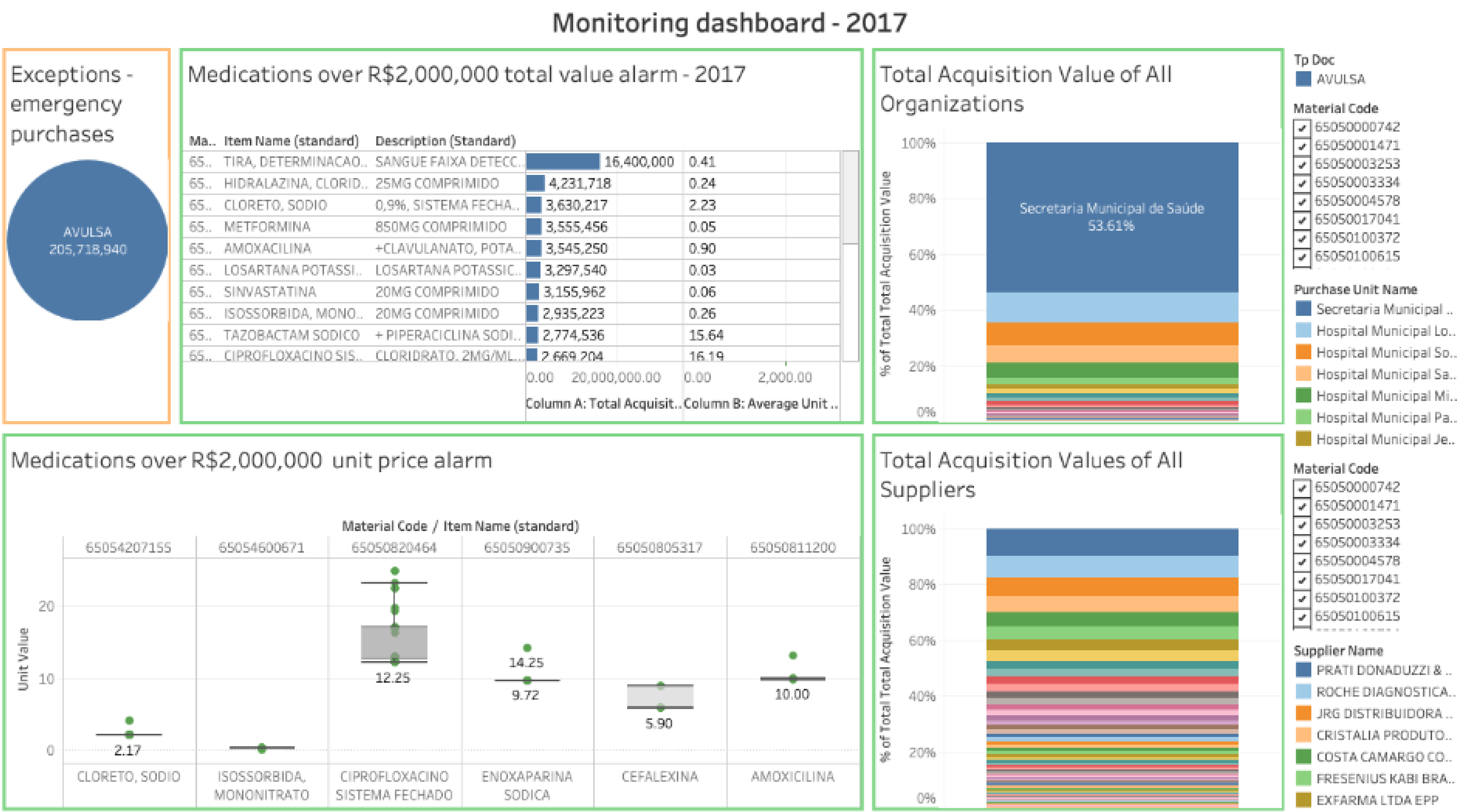
Continuous Monitoring Dashboard



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New York City Street Cleanliness: Apply Text Mining Techniques to Social Media Information

Huijue Kelly Duan[1]

Mauricio Codesso[2]

Zamil Alzamil[3]

[1]Rutgers, the State University of New Jersey
[2]Northeastern University
[3]*Majmaah University*

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Motivation

- NYC government performs a cleanliness inspection every year, the method has not changed for nearly 50 years
- NYC districts receive ratings of 90% or higher; therefore, NYC government rates majority of its streets as acceptably clean
- NYC residents increasingly contact DSNY via 311 about missing trash pickups, overflowing litter baskets, and dirty conditions

Monthly SCORECARD Community Board Report - July 2019

Percent of Acceptably Clean Streets (Citywide Totals) - 2019 / 07

Borough	Acceptable Streets %	Acceptable Streets % - Previous Month	Acceptable Streets % - Year Ago
Manhattan	96.4		96.6
Bronx	97.3		94.6
Brooklyn	98.3		94.0
Queens	98.7		97.7
Staten Island	100.0		98.0
Citywide Total	**98.4**		**96.3**

Objective

- Examine the social media information
  - ➢ to identify temporal trends and patterns of the cleanliness of NYC streets
  - ➢ to analyze whether crowdsourcing information is consistent with NYC cleanliness ratings
  - ➢ to assess the performance of municipal services via sentiment analysis

@nyc311 @NYCSanitation HARLEM 116th b/t 7th & 8th **street** is **trash** & rodent ridden. When is this going to stop? #nowyouknow #getittogether #foodbank #petopia #ctown #kingston

when I was out walking tonight a rat jumped in front of me and I accidentally kicked it .... it was ok but I think @**NYC**_DOT should study rat crosswalks between **street trash** collection sites and buildings to avoid future injuries #streetsafety

Im from **NYC**; Where once u **find parking**, U **cant** go out for the remainder of the day 😂😭😭

Workflow

Data Collection	→	Data Preparation	→	Relevancy Determination	→	Sentiment Analysis

Step 1 — Step 2 — Step 3 — Step 4

Step 1
- Twitter API (Streaming API)
- 6.8M collected (8/27/2018 - 5/22/2019)

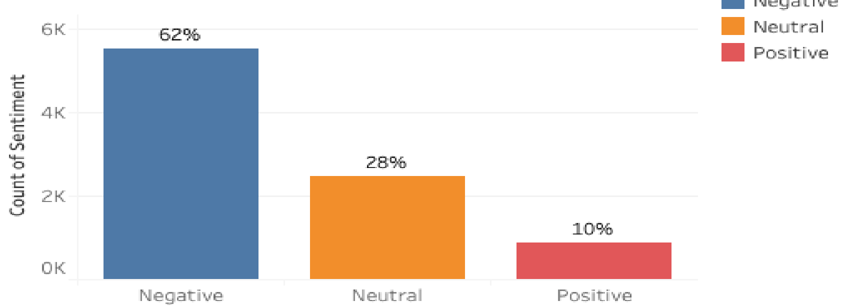
Step 2
- Data Cleaning
- Variable Selection and Aggregation
- Data Aggregation

Step 3
- Apply Keyword List
- Data Preprocessing
- Supervised Machine Learning
  - ❖ Naïve Bayes
  - ❖ Random Forest
  - ❖ XG Boost

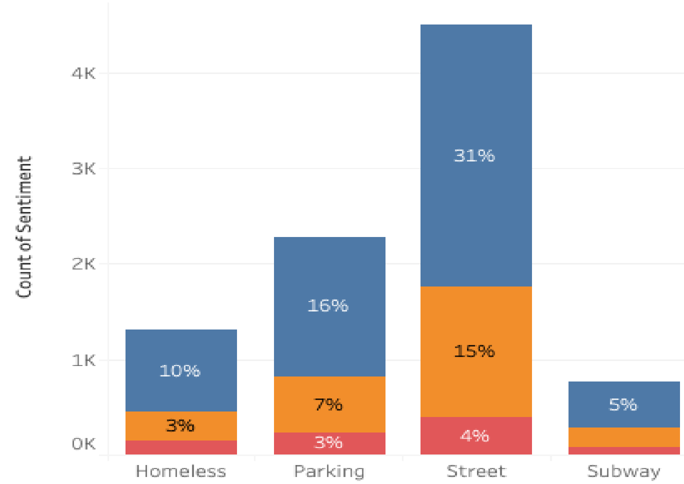
Step 4
- Negative
- Positive
- Neutral

Twitter Dashboard

Overall Sentiment



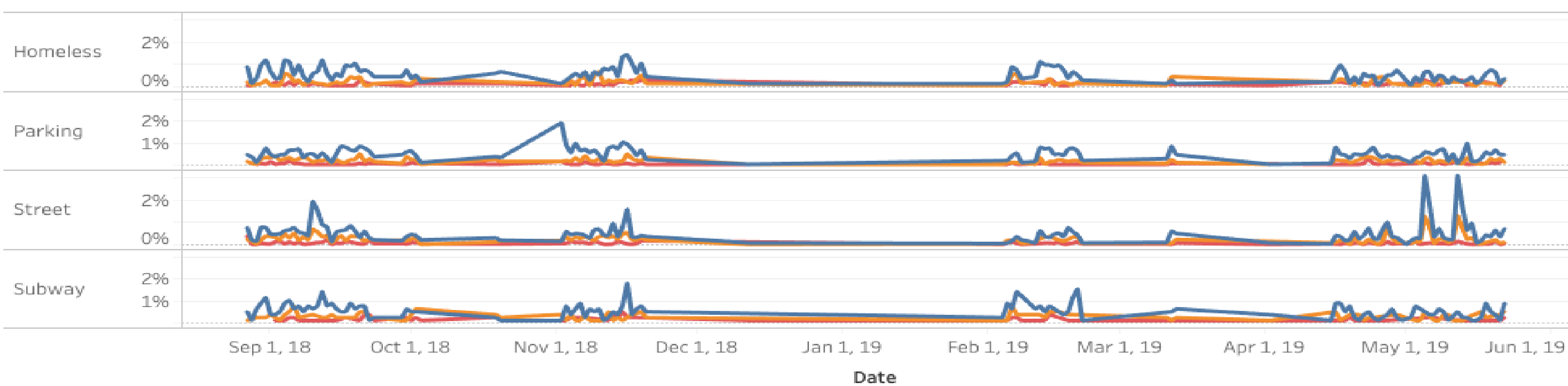
Sentiment by Category



Descriptive Statistics-Category

Sentiment	Homeless	Parking	Street	Subway	Grand Total
Negative	10%	16%	31%	5%	62%
Neutral	3%	7%	15%	2%	28%
Positive	2%	3%	4%	1%	10%

Time Series Analysis



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Continuous Intelligent Pandemic Monitoring (CIPM)

Huijue Kelly Duan

Hanxin Hu

Miklos Vasarhelyi

Accounting Information System

Rutgers, the State University of New Jersey

Research Objective

- Use measurement science (accounting), assurance science (auditing) to enhance pandemic responses
- This study aims to establish a Continuous Intelligent Pandemic Monitoring system (CIPM)
  - Validate the epidemic related numbers
  - Provide guidance to policymakers so that sufficient resources can be allocated to the upcoming high risky areas

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Data Collection

- Collect relevant exogenous and endogenous data sources
  - ✓ Total confirmed cases, Total deaths, Daily confirmed cases, Daily deaths, Total test, number of positive tests, etc.
  - ✓ Demographic density, Industrial jobs, Industrial establishments, % of urban population, Territorial extension of the municipality, list of municipalities by region, Volume of passengers carried, Transported cargo flow, GDP, etc.
  - ✓ Apple mobility, Google trends, Official announcements, Tweets, Unemployment claims filed, etc.

Model Construction

- Establish a systematic and continuous COVID-19 monitoring model
  - ✓ Use time series and machine learning algorithms to perform predictive analytics
  - ✓ Apply clustering approach to perform cross sectional analysis
  - ✓ Simulate the Epidemic models

Alert

- Incorporate audit risk assessment to establish an alert system
  - ✓ The number reasonableness
  - ✓ Disease severity
  - ✓ Regional severity
  - ✓ The policy sufficiency

Action Recommendations

- Present guidance to policymakers based on the simulation results
  - ✓ Number validation
  - ✓ Peer groups evaluation
  - ✓ Policy simulations

Figure 1. Continuous Intelligent Pandemic Monitoring Framework

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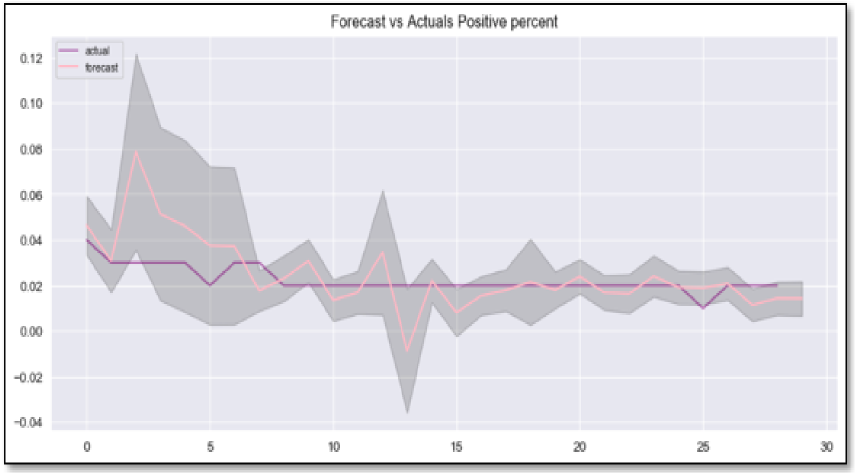


Figure 2-1: Predicted positive test ratio vs Actual positive ratio

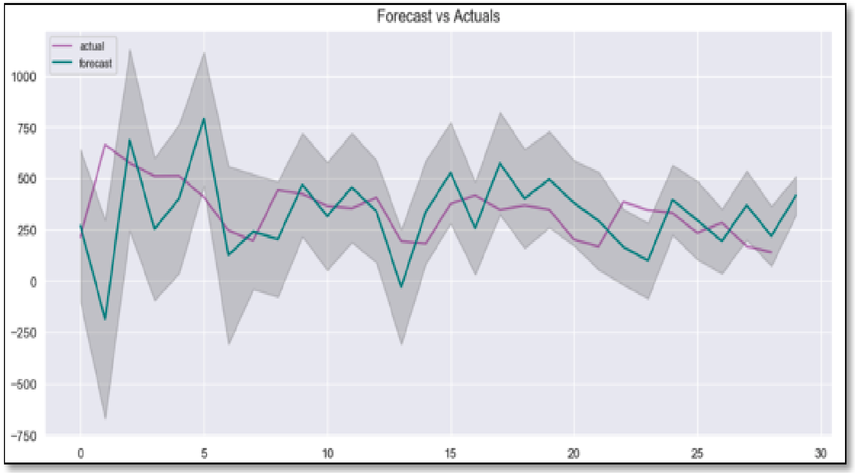


Figure 2-2: Predicted confirmed cases vs Actual confirmed cases

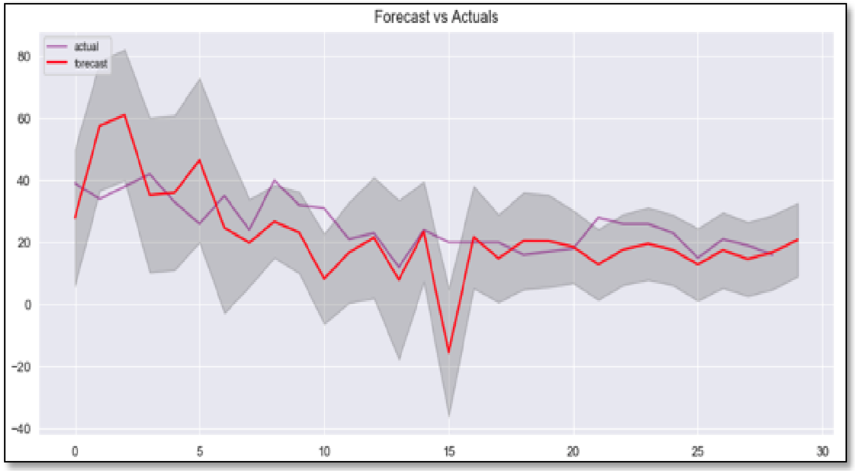


Figure 2-3: Predicted death cases vs Actual death cases

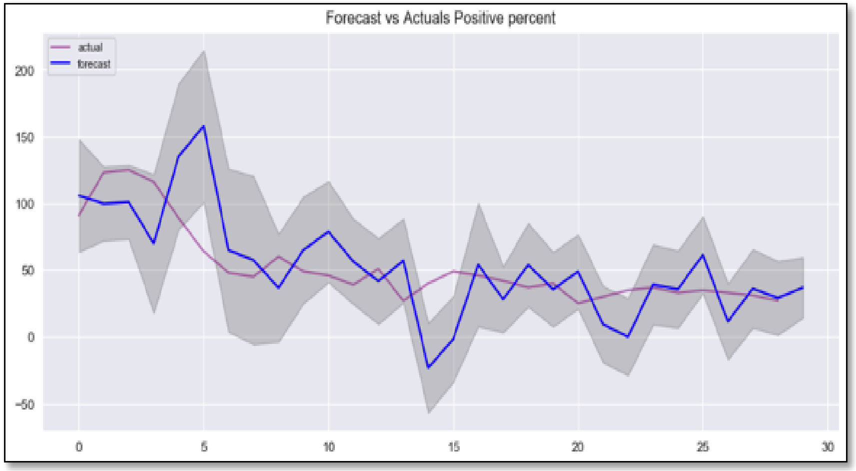
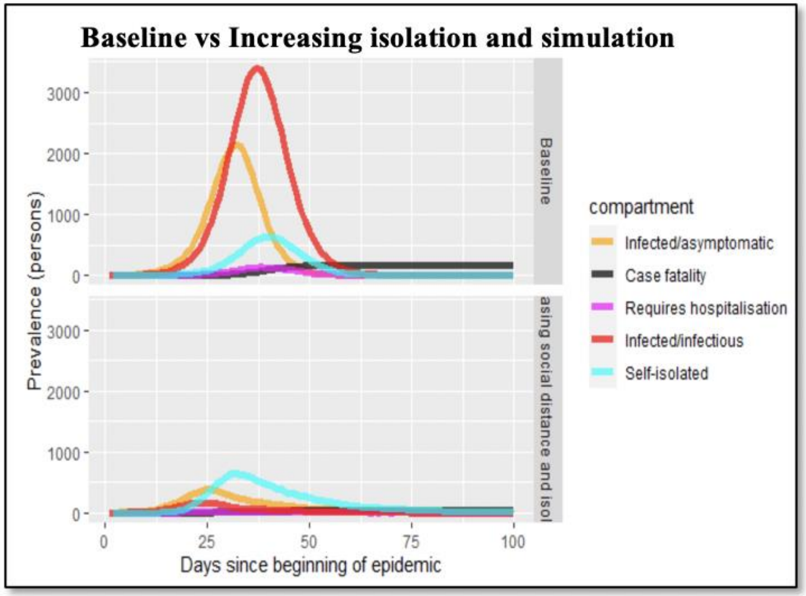
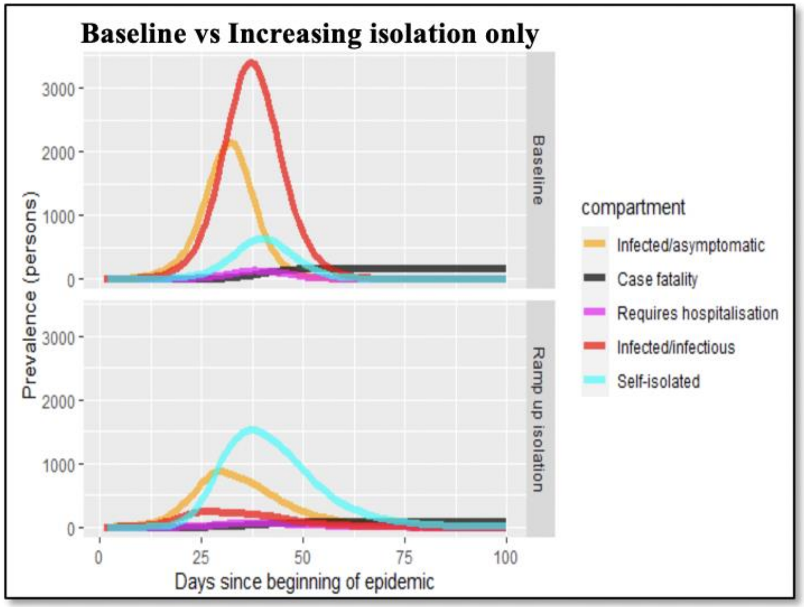


Figure 2-4: Predicted hospitalizations vs Actual hospitalizations





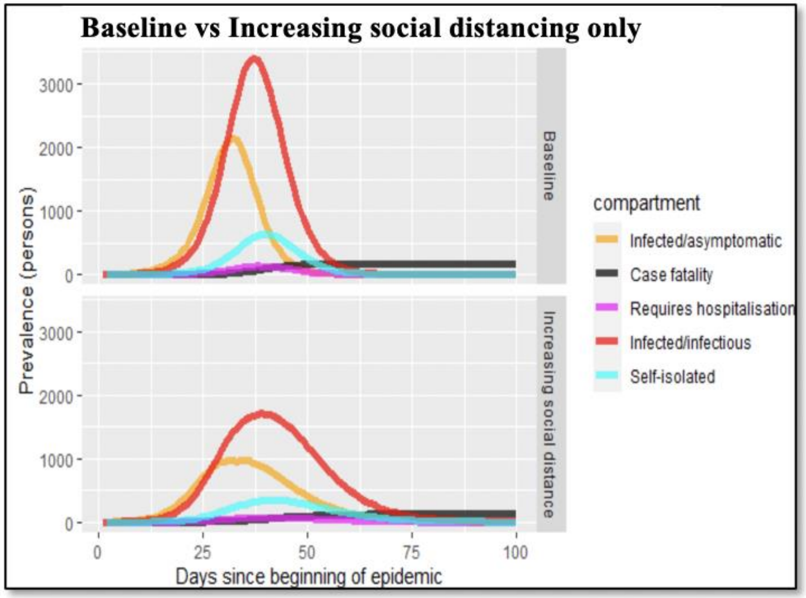


Figure 3: Use SEIQHRF model to simulate the impacts of different social interventions policies assuming the total number of population is equal to 10000. When enforcing self-isolation and social distancing, we can better control the transmission of COVID-19.

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A Machine learning approach To measuring audit quality With surprise scores:
Evidence from China

Authors:
Hanxin Hu (Rutgers),
Ting Sun (TCNJ),
Miklos A. Vasarhelyi (Rutgers),
Min Zhang(Renmin University, China)

Data

- **Dependent variables (we developed a prediction model for each dependent variable)**:
  - Net income adj
  - Total assets adj
  - Total liability adj
  - Stockholders' equity adj
  - Income before income tax adj
  - Income tax adj
  - nonclean opinion
  - Restatement(misstatement)
- **Independent variables (example: using net income adjustment as the dependent variable):**

  Companies' characteristics (27 variables)

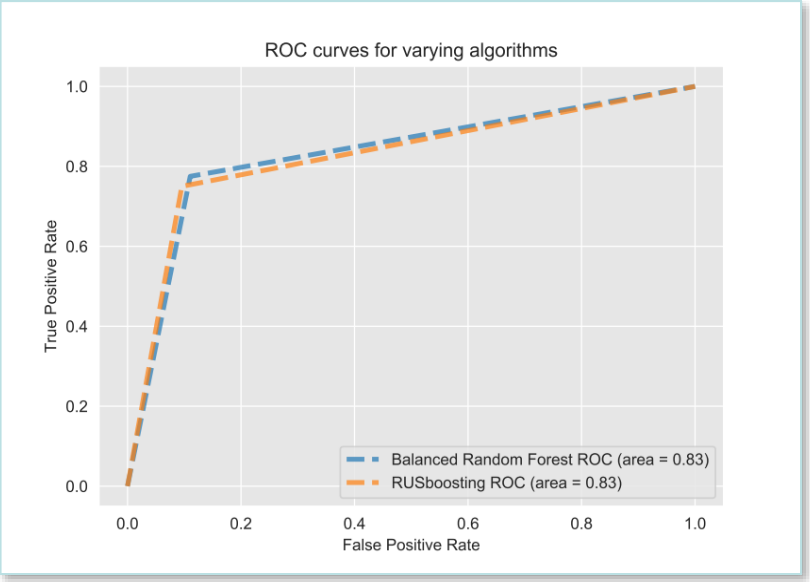
  Audit firms' characteristics (28 variables), e.g., revenue, subsidiaries, net assets

  Audit partners' characteristics (15 variables), e.g., education, age, gender, birthplace, title
- **Data sources:** Chinese Ministry of Finance, CICPA (Chinese Institute of CPAs), CSMAR(China Stock Market & Accounting Research Database)
- **Research period:** 2010-2017
- **Data size:** 11574
- **Data splitting:** training (6626 observations) /test (1325 observations)/application (3546 observations)

Machine learning algorithms

- Random Forest
- SVM
- Gradient boosting
- XGBoosting
- Deep neural networks
- Logistic regression (the bench mark algorithm)
- RUSboosting
- Balanced Random Forest

Prediction Results



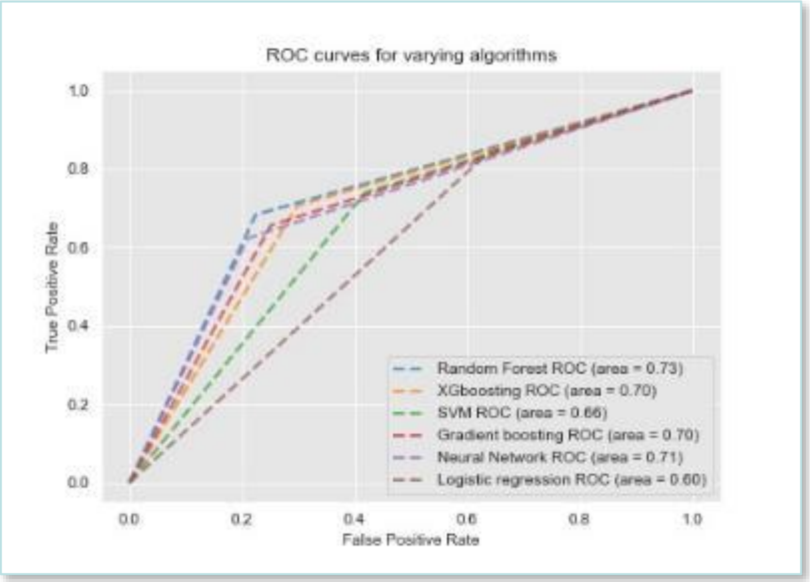


Figure 1: ROC AUC for varying algorithms when "nonclean opinion" is the target variable

Figure 2: ROC AUC for varying algorithms when "net income adjustments" is the target variable

Application: Results

1. Nonclean audit opinion; Nonclean opinion surprise score; The aggressiveness score

Independent variable	Estimated coefficient	P value
Nonclean audit opinion	-27.78	0.960933
Nonclean opinion surprise score (ML)	*3.467*	*7.84e-13 ****
The aggressiveness score (Logistic)	*0.3958*	0.008126 **

2. Net income adjustment; Net income adjustment surprise score; The aggressiveness score

Independent variable	Estimated coefficient	P value
Net income adjustment	-0.01700	0.853533
Net income adjustment surprise score (ML)	*0.01105*	*0.911363*
The aggressiveness score (Logistic)	*0.02298*	*0.812480*

Note: the regression results for other audit adjustment variables are similar to those for net income adjustment.

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Multidimensional Clustering for audit fault detection

Sutapat Thiprungsri
Miklos A. Vasarhelyi

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Metlife

- Data stream of over 200K wire transfers
- Data only currently available for the wires and the records possess little information
- Little context knowledge of the major feeding streams
- No fraud training data available
- Worked during the audit supplementing the audit team work
- Developed a series of data filters relating to specific conditions and trends
- Working on an aggregate weighting model
- Need in the field verification of picked data

Insurance monitoring and assessment

Wire transfers

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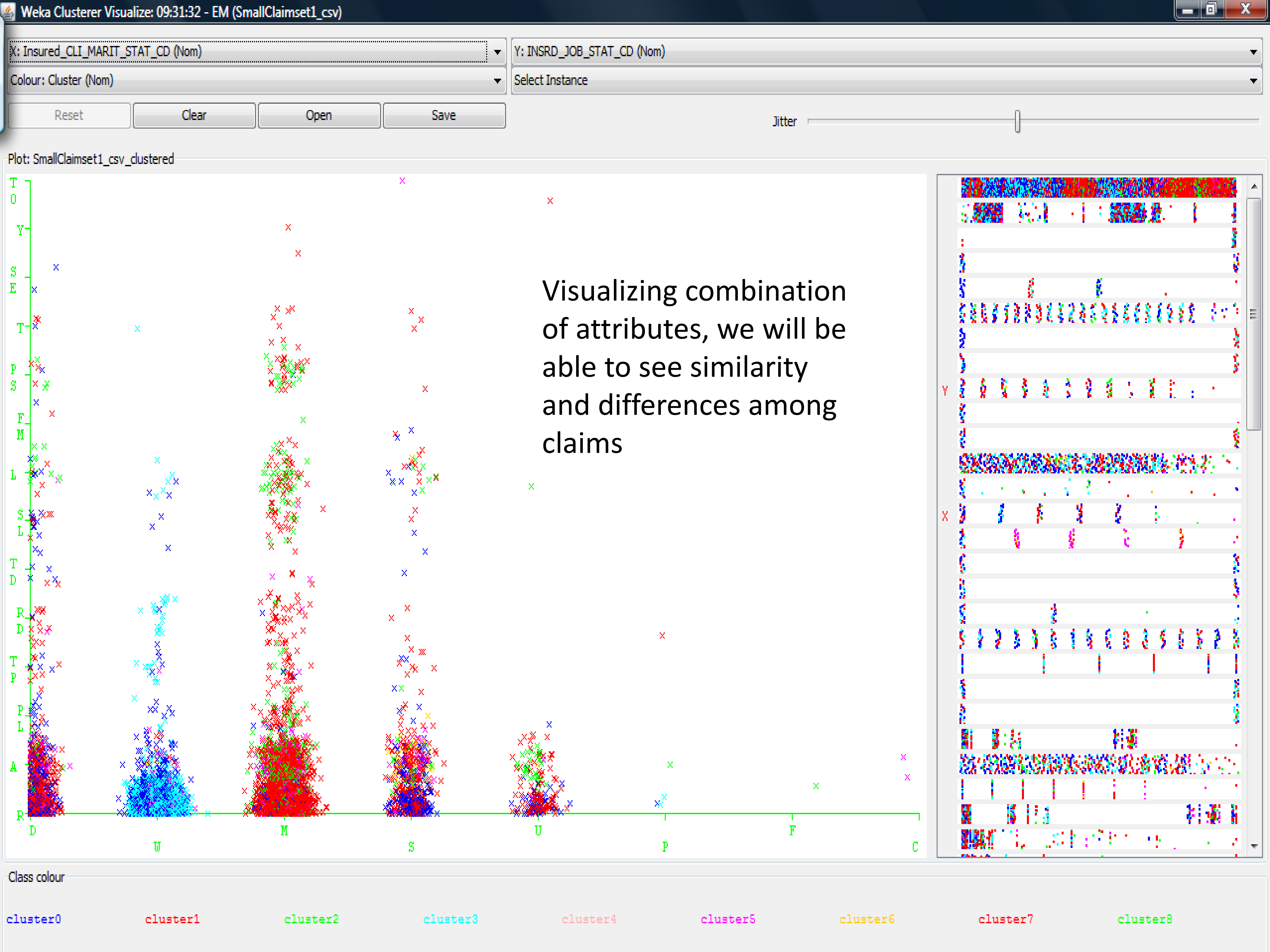
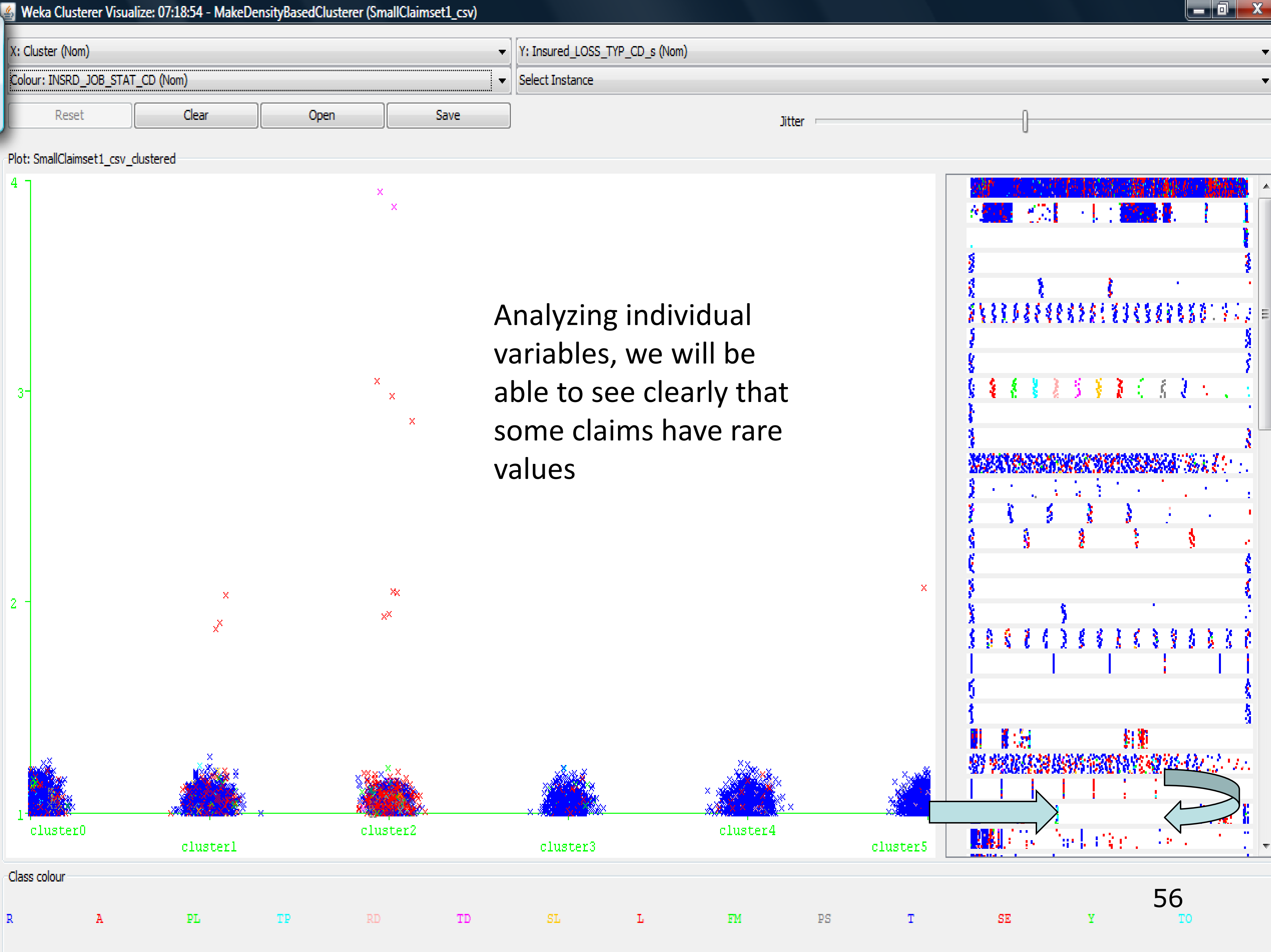

Weka Clusterer Visualize: 09:31:32 - EM (SmallClaimset1_csv)
X: Insured_CLI_MARIT_STAT_CD (Nom)
Y: INSRD_JOB_STAT_CD (Nom)
Colour: Cluster (Nom)
Select Instance
Reset
Clear
Open
Save
Jitter
Plot: SmallClaimset1_csv_clustered
Visualizing combination of attributes, we will be able to see similarity and differences among claims
Class colour
cluster0
cluster1
cluster2
cluster3
cluster4
cluster5
cluster6
cluster7
cluster8



Analyzing individual variables, we will be able to see clearly that some claims have rare values

Conclusions

- A wide range of analytic methodologies exists to treat any data rich problem
- Change is very slow rule to anachronistic regulations and embedded interests, as well as lack of training within organizations
- CarLab develops an approach for each project it does
  - If you know what you are doing you are not doing research (Albert Einstein)
- The World Bank has the scope and nature to be an ideal location for experimental analytics using, big data, exogenous variables, machine learning, and a set of out-of-the-box sensing and measurement methods