

# Abnormality in Non-Profit Financial Data

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# Determining the right Non-Profit is hard.

- Historically Limited Data Available
- Little Incentive to release or collect data
- Difficult to measure performance

But determining the organization not to invest in might be easier.

## Objective

Create an outlier model that will detect higher risk organizations that might need additional scrutiny and see if we can make any inferences.

- Non-Profit Organization are required to file form 990 with the IRS to keep their tax exempt status
- Recently the IRS released the full form for all 220,000+ nonprofits that filed and posted parsable xmls on Amazon Web Services

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# Featurize and Clean

~220,000 Nonprofits

~250 Features

Everything from  
Real Estate holdings  
to Indoor tanning  
expenses



~50,000 Nonprofits

Organizations with  
more 1,000,000  
Revenue and 500,000  
Donations

With  
features

## Structure

1. Executive Compensation

2.Leverage

3.Solvency

## Accounting Manipulation

4.Deferred Expenses Ratio

5.Deferred Revenues Ratio

6.Depreciation Rate

## Performance Metrics

7.Fundraising Efficiency

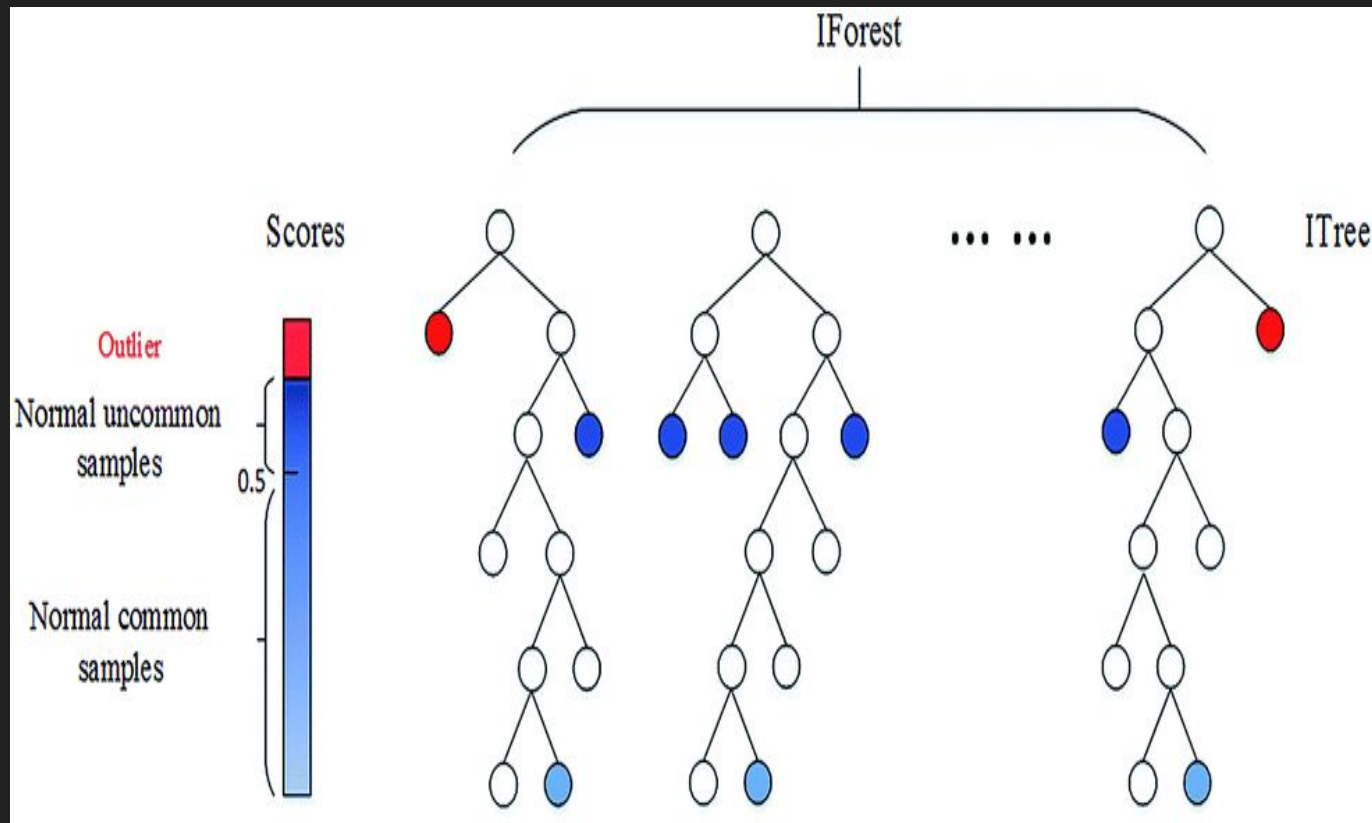
8.Surplus Margin

# Isolation Forest Model

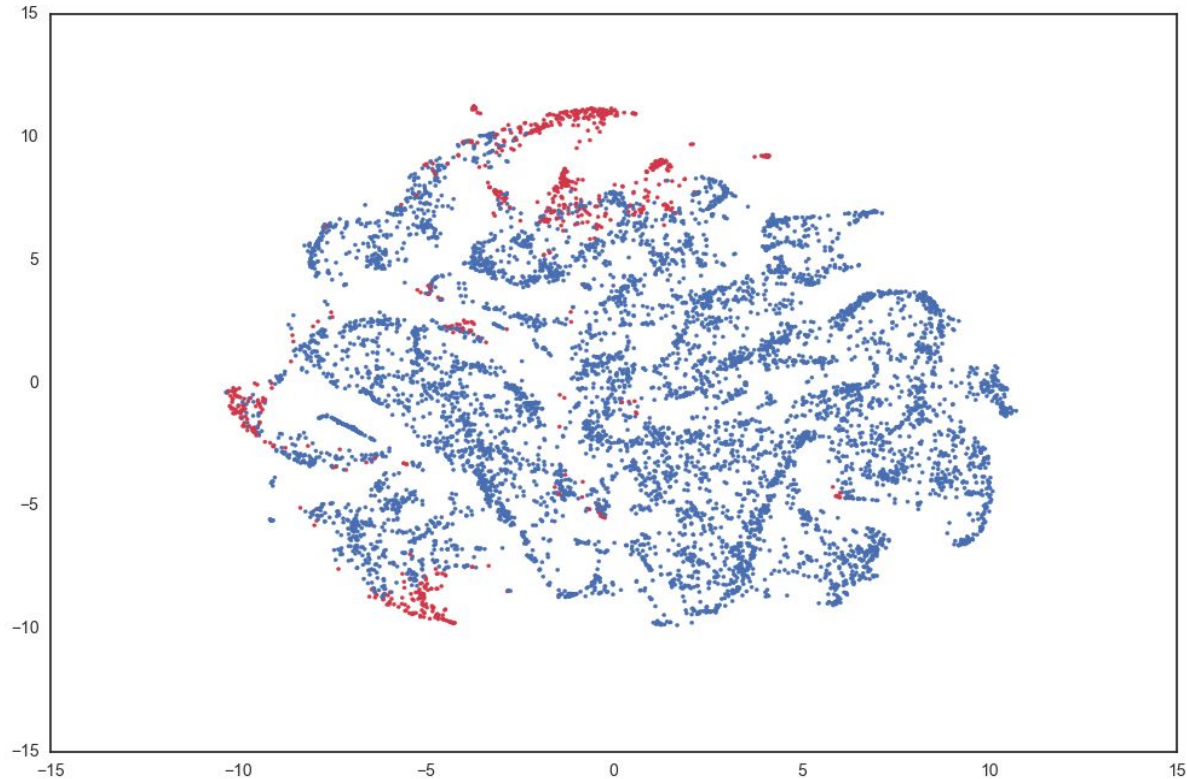
- Good way to identify outliers in Multidimensional data sets

## How it works

- Randomly select a feature and Randomly select a split between the min and max of the feature
- Split until observation is isolated
- Closer the terminal node is root node the more abnormal the observation is
- Perform on a number of trees and average the distances to get an abnormality score



# TSNE Display showing the different clusters of outlier organizations



# What are we detecting?

Structure
1. Executive Compensation
2.Leverage
3.Solvency
Accounting Manipulation
4.Deferred Expenses Ratio
5.Deferred Revenues Ratio
6.Depreciation Rate
Performance Metrics
7.Fundraising Efficiency
8.Surplus Margin

Seems we are identifying non-profits that share similar characteristics and can be classified into distinct clusters

- Low (Assets, Liabilities), High (Revenue and Expenses) cluster - identified by structure metrics
- The Bad Cluster - identified by high judgment metrics

# Thank You

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# Appendix:

## OLS Regression on Abnormality Score

### OLS Regression Results

Dep. Variable:	AS	R-squared:	0.241
Model:	OLS	Adj. R-squared:	0.241
Method:	Least Squares	F-statistic:	2037.
Date:	Tue, 18 Oct 2016	Prob (F-statistic):	0.00
Time:	23:20:18	Log-Likelihood:	35193.
No. Observations:	51354	AIC:	-7.037e+04
Df Residuals:	51346	BIC:	-7.030e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
field1	-2.06e-06	4.09e-07	-5.034	0.000	-2.86e-06 -1.26e-06
field2	0.0010	0.000	7.243	0.000	0.001 0.001
field3	-2.896e-07	1e-07	-2.884	0.004	-4.86e-07 -9.28e-08
field4	0.1273	0.004	34.429	0.000	0.120 0.135
field5	0.0446	0.003	14.028	0.000	0.038 0.051
field6	0.2221	0.002	95.015	0.000	0.218 0.227
field7	0.0531	0.001	40.564	0.000	0.051 0.056
field8	-8.589e-08	9.12e-08	-0.942	0.346	-2.65e-07 9.28e-08

Omnibus:	28041.573	Durbin-Watson:	0.926
Prob(Omnibus):	0.000	Jarque-Bera (JB):	40966739.942
Skew:	1.074	Prob(JB):	0.00
Kurtosis:	141.351	Cond. No.	4.14e+04

#### Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.14e+04. This might indicate that there are strong multicollinearity or other numerical problems.

# Appendix:

## Random Forest Feature Importance

```
In [101]: log_model.forest_analysis(filepath, 'outlier_IF')  
Out[101]:  
array([ 0.14680097,  0.14777542,  0.21802028,  0.16047295,  0.0785647 ,  
        0.12347648,  0.08946984,  0.03541936])
```