Campaign Consulting Proposal

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Agenda

- Introduction
- Voter Prediction Model
- Demographic Model
- Donation Rates
- Voter Clustering Model
- Services and Product Offerings

Introduction - Background

Over the past several years, statistical modeling and analytics have become increasingly critical to major campaigns across the country

OBAMA
BIDEN

2012

2016

- "In 2012, the Obama Campaign used data analytics and experimental methods to assemble a winning coalition vote by vote"
- "The campaign didn't just know who you were; it knew exactly how it could turn you into the type of person it wanted you to be

Source: "How Obama's Team used Big Data to Rally Voters" https://www.technologyreview.com/s/509026/how-obamas-team-used-big-data-to-rally-voters/

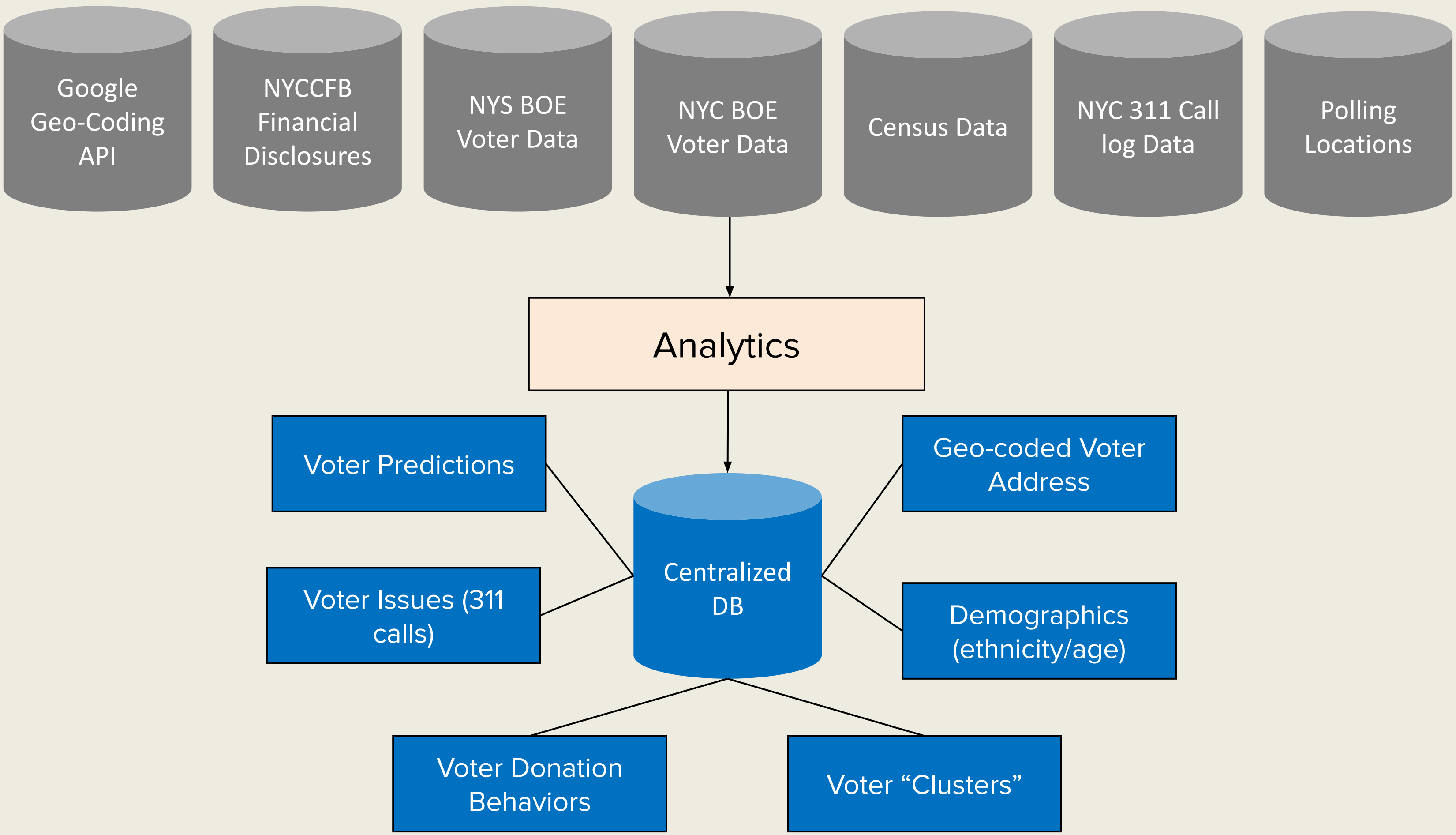
- "Analytics, as it did in 2012, is playing an important role for mass voter persuasion in the U.S. presidential race"
- "It's a numbers game: Predictive analytics targets campaign activities, strengthening a campaigns army of volunteers by driving its activities more optimally"

Source: "How Hilary's Campaign Is (Almost Certainly) Using Big Data" https://blogs.scientificamerican.com/guest-blog/how-hillary-s-campaign-is-almost-certainly-using-big-data/

However, city-level elections have not seen the same proliferation of data and analytics in campaigns

Introduction - Background

Several data sources and tools offer city-level campaigns the same opportunity to take advantage of the data science revolution



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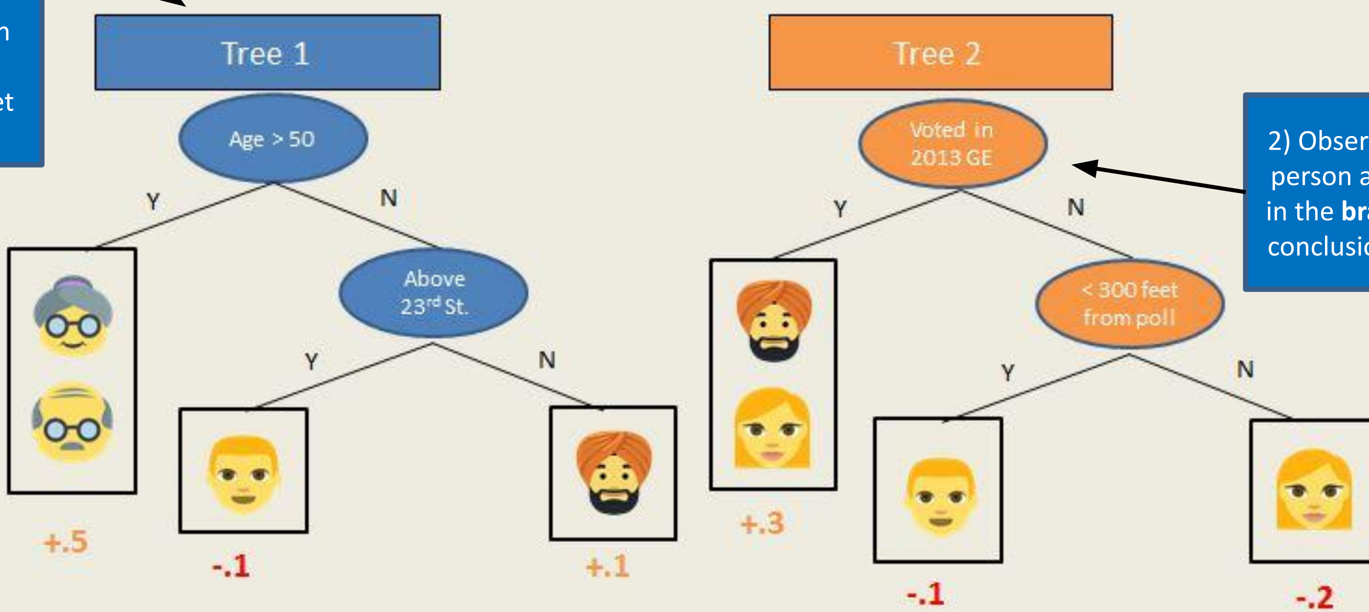
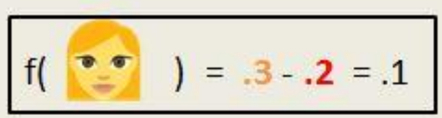
Voter Prediction Model – Decision Tree

One way we can apply analytics to city-level elections is to predict voting behavior for individuals. This can be done by using a regression tree-based machine learning model:

1) Decision tree learning uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value



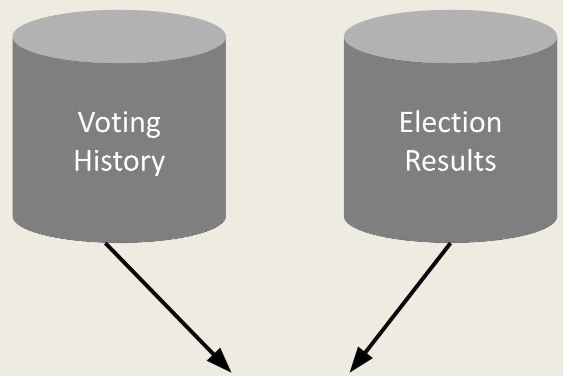
2) Observations about a person are represented in the **branches** to make conclusions about them



3) This allows us to statistically predict the likelihood of an individual voter's turnout

Voter Prediction Model

Using voter history and previous elections results, we can try to predict historical and future voting behavior for each registered voter



Voter ID	Turnout	Rosie Mendez	Richard Del Rio
123456	.91	.56	.27

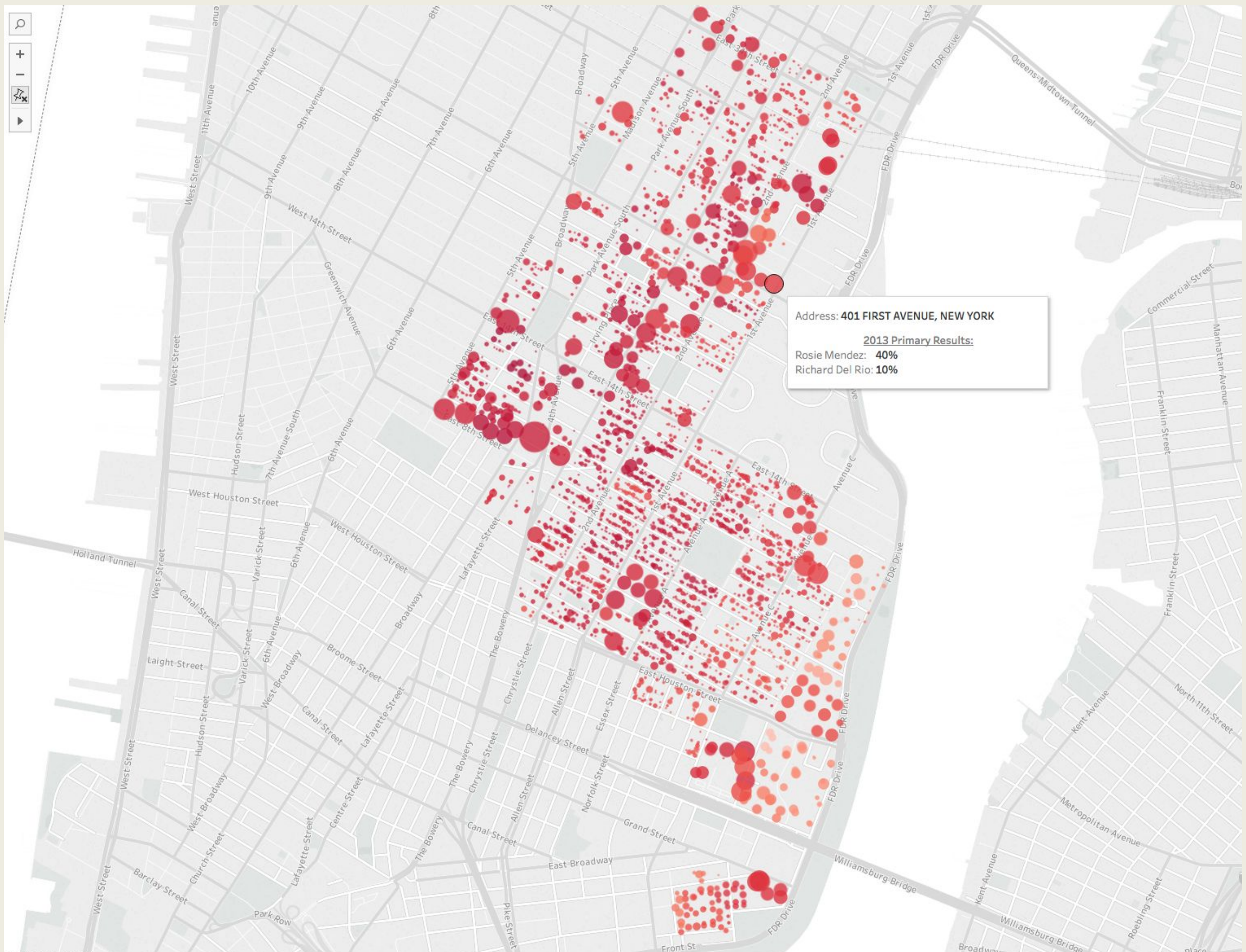
% likelihood person will vote in specific election

% likelihood person voted for Rosie Mendez in 2013 Primary

% likelihood person voted for Richard Del Rio in 2013 Primary

Voter Prediction Model

These models can be used to predict turnout and likely voting choices from previous elections



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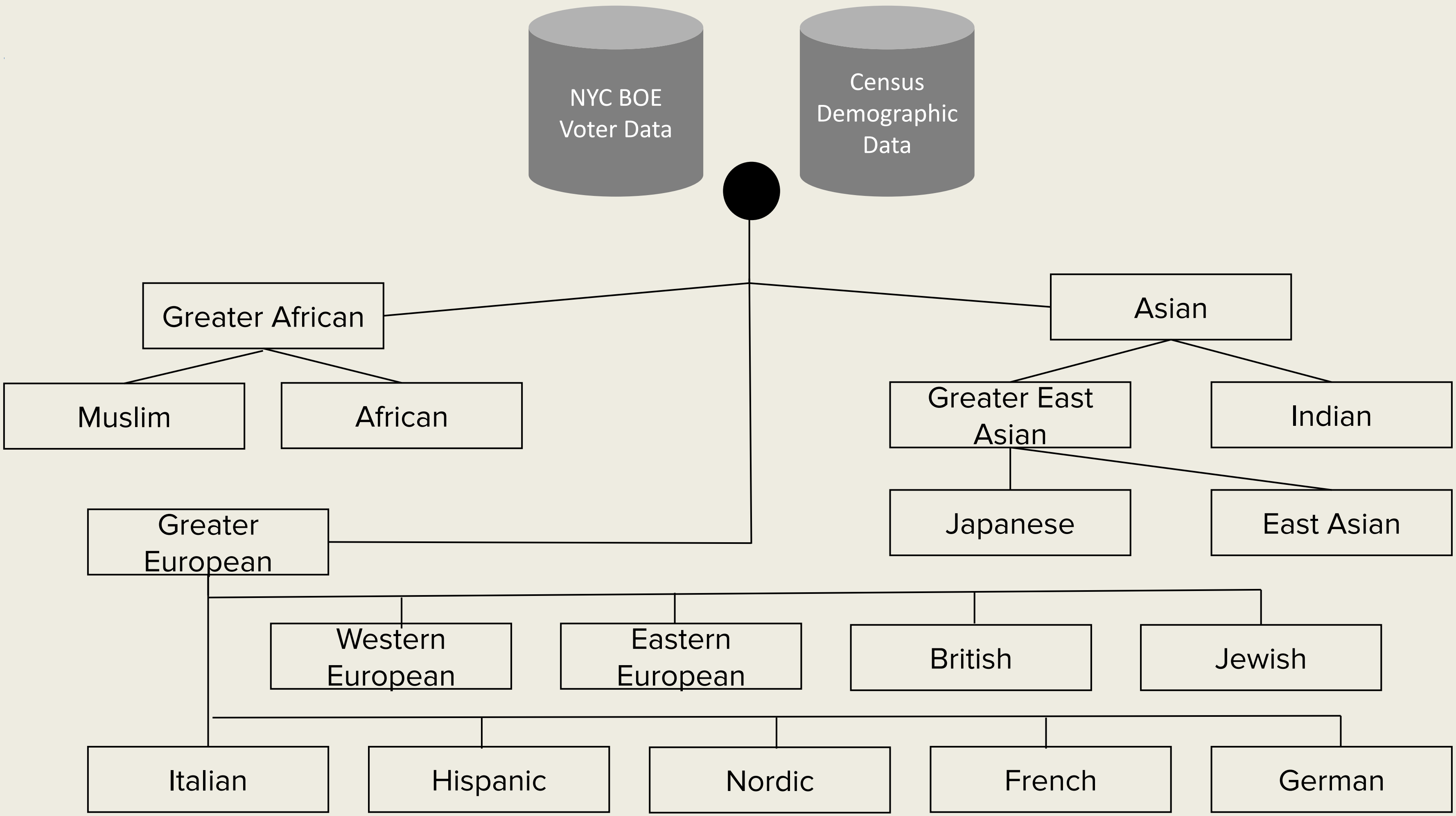
- 311 Call Analysis10 min
- Services and Product Offerings 10 min

Demographic Model

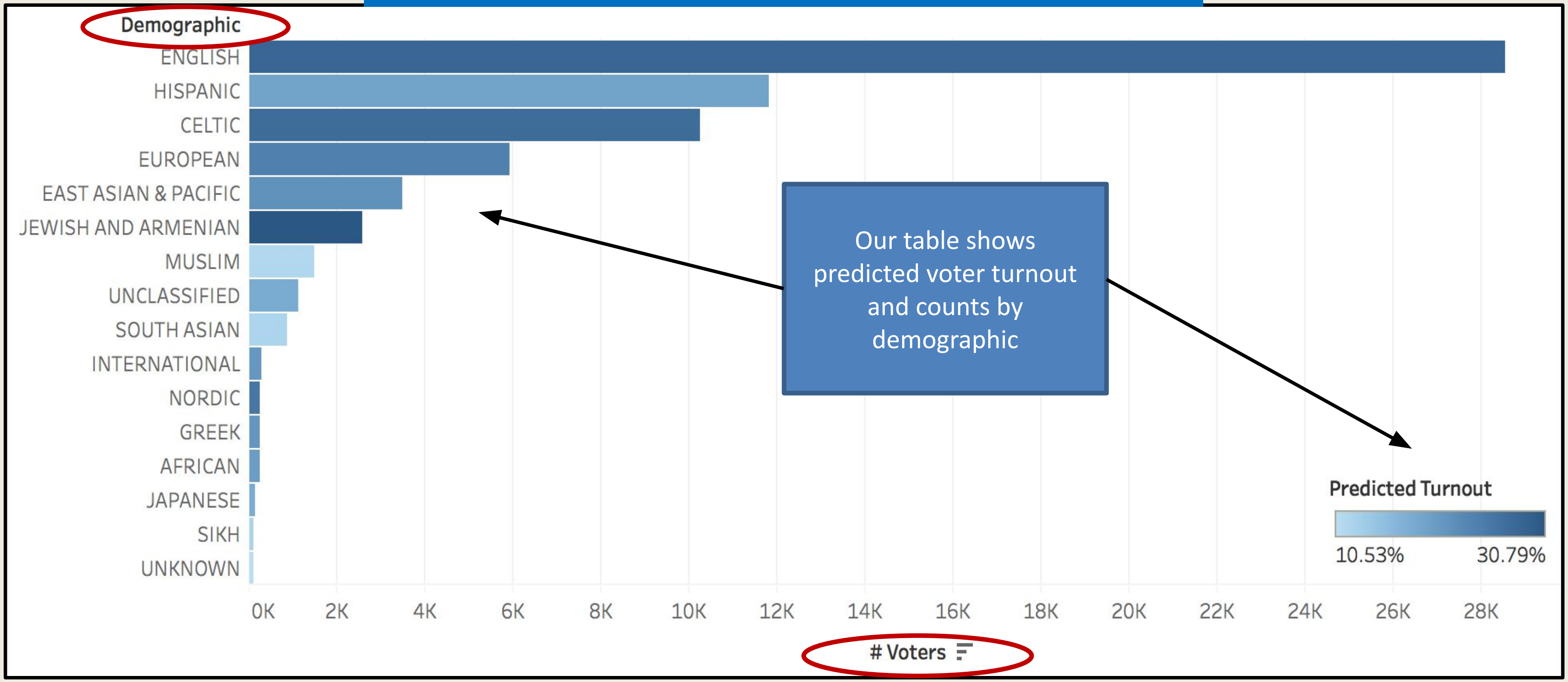
Using similar machine learning models, we're able to classify and predict voter demographics based on names and age



Demographic Model – Sample Results

Understanding voter demographics allows our predictions to be more accurate and granular.

District 2: Predicted Voter Turnout

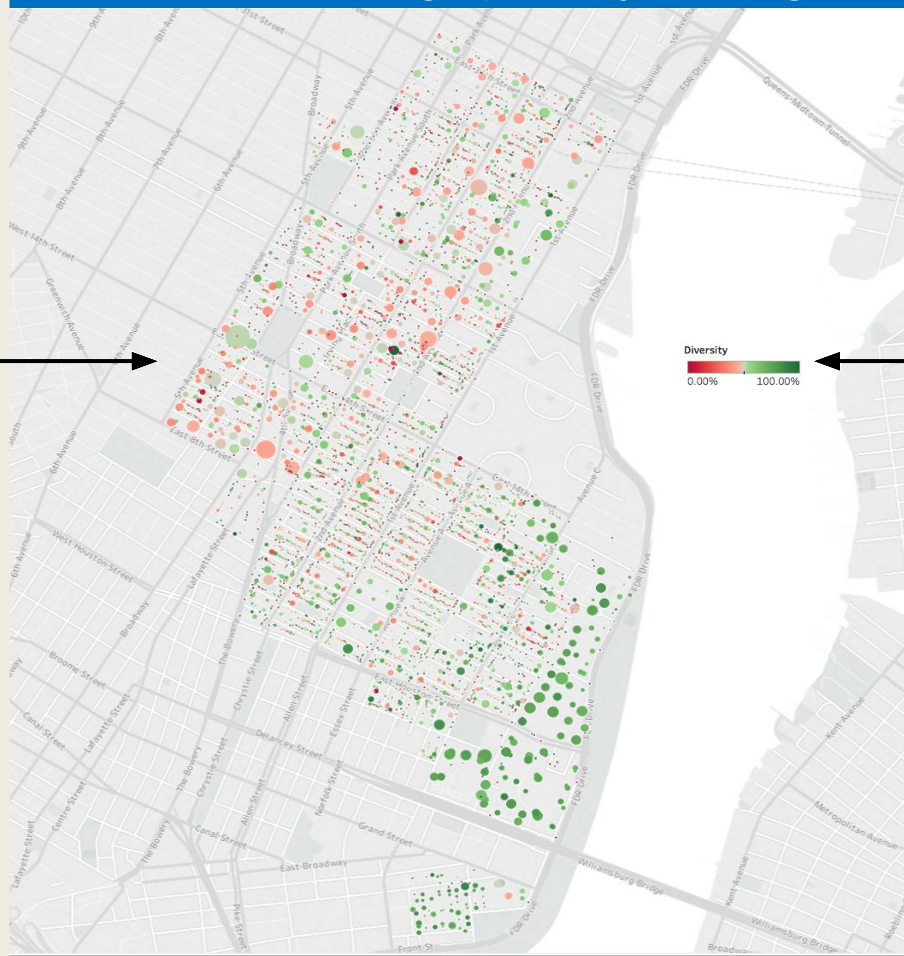


More granular results enables opportunities for unique and personalized voter outreach efforts (i.e. personalized direct mail/email, targeted phone banking and canvassing, custom campaign event planning

Demographic Model – Sample Results

We can also strategize voter outreach efforts around demographics of specific buildings

District 2 Demographics by building



Predicted Turnout
(circle size)

Demographic makeup
(color-scale).
Red=greater uniformity

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Donation Analysis

Combining NYCCFB data with voter data adds another layer to our analysis. Understanding where donations come from can help focus campaign efforts

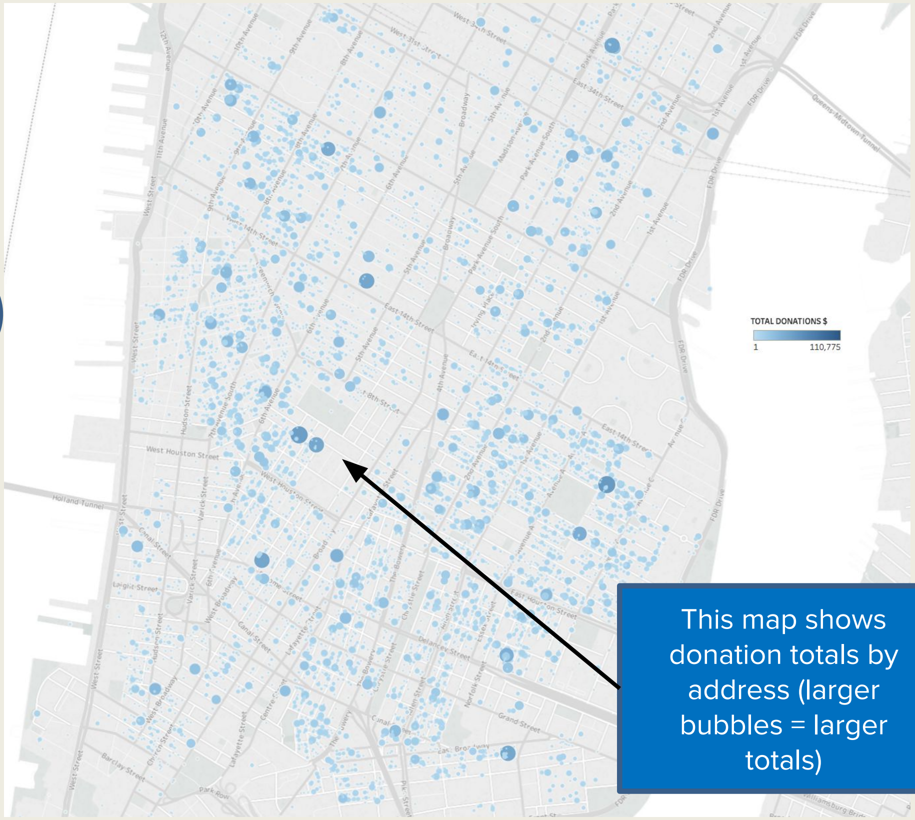
Donation Analysis can help us answer new types of questions:

Which primary voters likely donated to a competitor?

How can we focus our efforts to grow our donor base?

Which neighborhoods are our competitors targeting?

Manhattan Registered Voter Donation Totals by Address



This map shows donation totals by address (larger bubbles = larger totals)

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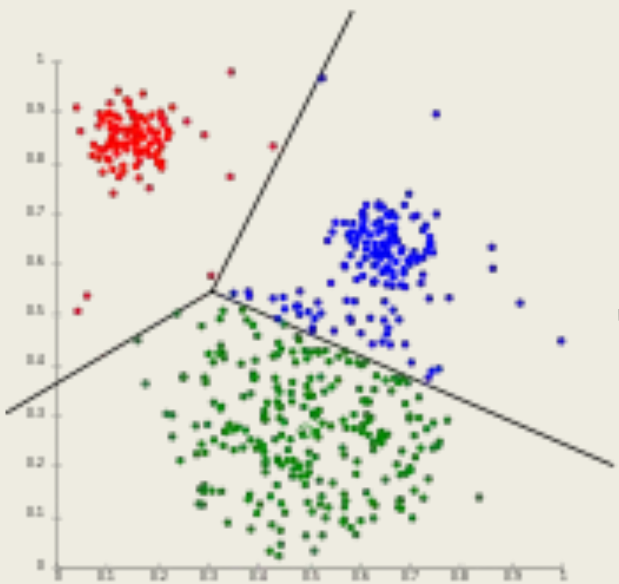
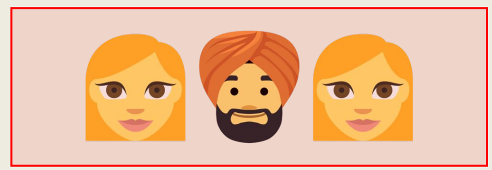
Voter Clustering Model

Using a machine learning method called k-means clustering, we can segment voters into unique clusters based on statistically significant data points

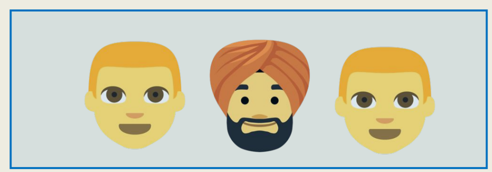
K-Means Clustering



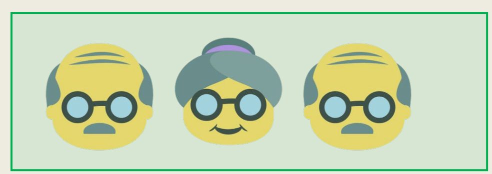
Sample Voter Clusters



Avg. Age: 28
Turnout Prediction: 20%
Female: 66%
Hispanic: 8%



Avg. Age: 38
Turnout Prediction: 40%
Female: 26%
Hispanic: 28%



Avg. Age: 68
Turnout Prediction: 60%
Female: 46%
Hispanic: 12%

Voter clusters can be used to create customized voter outreach efforts (i.e. personalized direct mail/email, targeted phone banking and canvassing, custom campaign event planning

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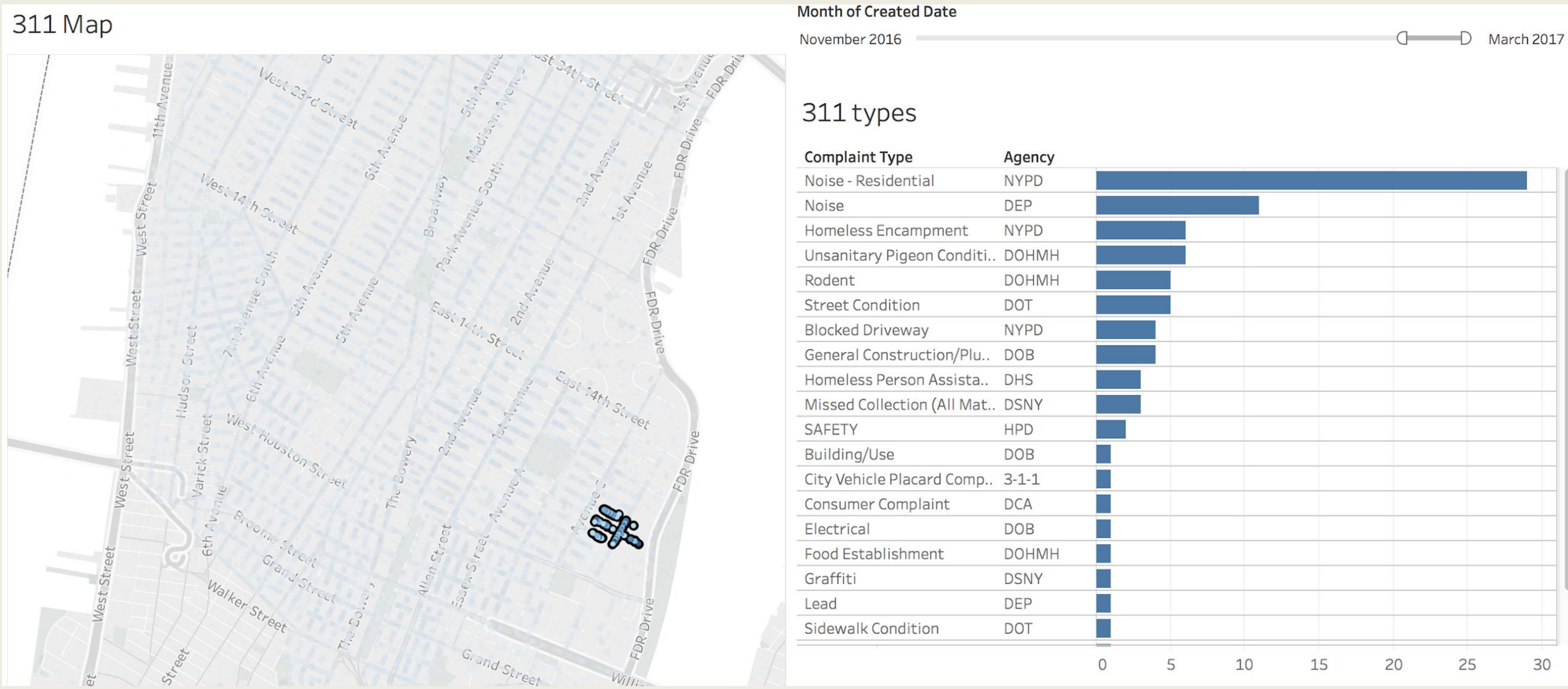
311 Call Analysis

By combining 311 call data with voter data, we can uncover insights on issues that each voter uniquely faces



Connecting 311 calls complaint types to voter data can help us understand issues unique to a given district or individual voter

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Summary

These models and analytics have several areas that can help a New York City Council Campaign win an election

Strategy

- Understanding Issues
- Donor Base Growth
- Voter density
- Voter Demographic composition

Targeting

- GOTV Efforts
- Customized Messaging
- Petition Gathering
- Online Ads/Direct Mail

Services and Product Offerings

Offering	Tier 1	Tier 2	Tier 3
Individually priced tools	●	●	●
All tools (discounted)	○	●	●
Raw Data	○	◐	●
Custom Reports	○	◐	●
Exclusive access within campaign district	○	○	●

Appendix

Voter Prediction Model - Accuracy

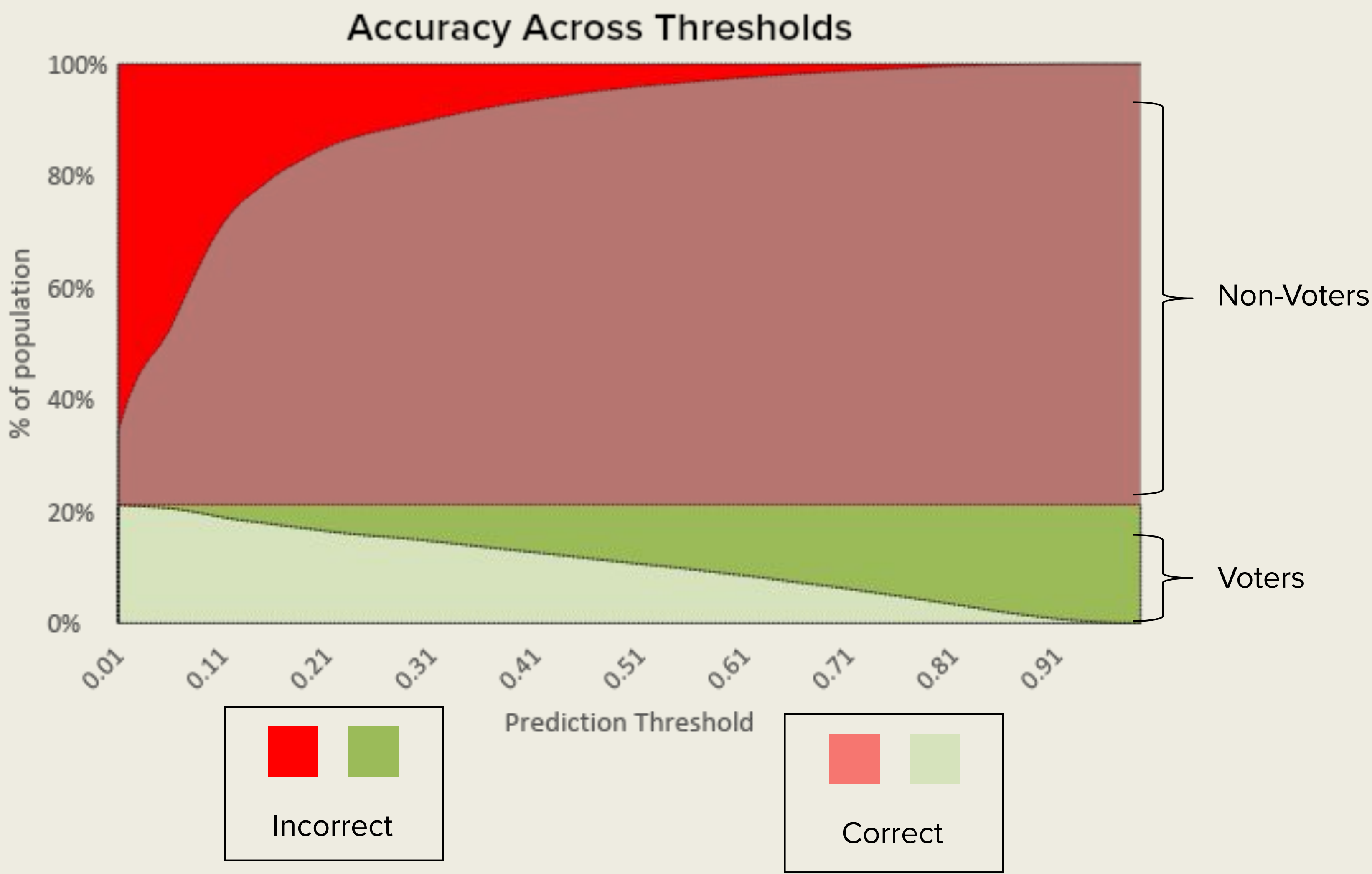
Understanding how to measure the of accuracy these models is important before building out further use cases:

Typical Model Performance (voter population of 100)

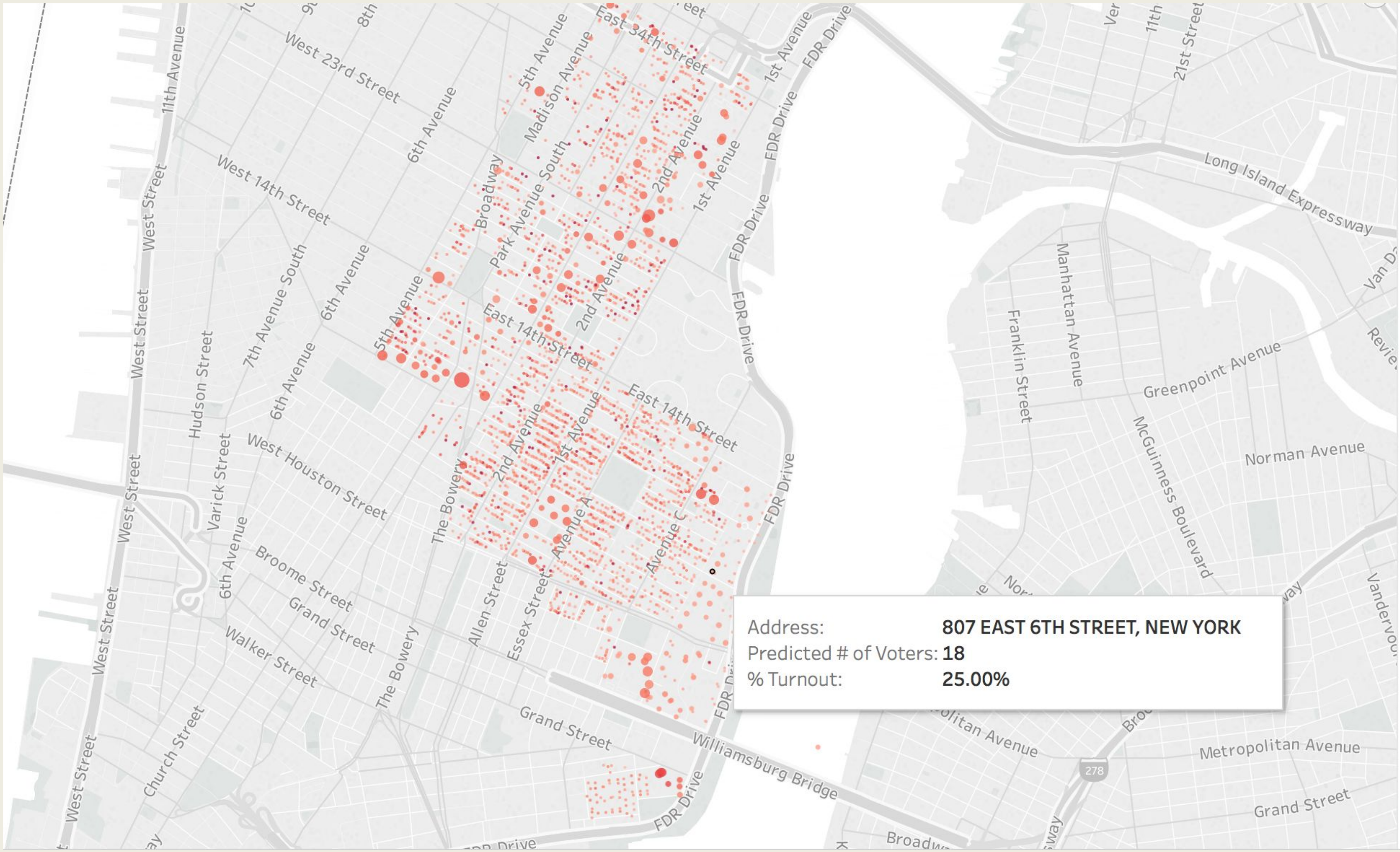
		Predictions		
		Vote	No-Vote	
Actuals	Vote	13	8	21
	No-Vote	7	72	79
		20	80	

Voter Prediction Model - Accuracy

Depending on how these predictions are used, different measurements of accuracy offer unique tradeoffs:



Use Case #1: targeting specific locations based upon likely voters



Use Case #2: targeting specific voters for outreach efforts

Voter Name	Voter Prediction	Address	Rapartment	District	Gender	Demographic	Sboeid	Prediction Score
JANE ASH	Voter	331 EAST 29TH STREET, NEW YORK	13F	2	F	ENGLISH	NY000000000378..	0.406
JANE ASHE	Non-Voter	633 EAST 11TH STREET, NEW YORK	12A	2	F	ENGLISH	NY000000000375..	0.228
JANE ATTIAS	Non-Voter	34 EAST 10TH STREET, NEW YORK	5 FL	2	F	EUROPEAN	NY000000000510..	0.144
JANE AUGUSTINE	Voter	346 EAST 18TH STREET, NEW YORK	3C	2	F	ENGLISH	NY000000000377..	0.579
JANE BAYARD	Voter	59 4TH AVENUE, NEW YORK	8B	2	F	ENGLISH	NY000000000378..	0.610
JANE BOBET	Non-Voter	215 EAST 4TH STREET, NEW YORK	17	2	F	HISPANIC	NY000000000545..	0.085
JANE BORKOW	Voter	229 EAST 11TH STREET, NEW YORK	16	2	F	ENGLISH	NY000000000375..	0.910
JANE BOWIE	Voter	331 EAST 29TH STREET, NEW YORK	12 H	2	F	CELTIC	NY000000000376..	0.830
JANE BUCHANAN	Non-Voter	335 EAST 13TH STREET, NEW YORK	9	2	F	CELTIC	NY000000000517..	0.103
JANE BURKE	Non-Voter	171 EAST 2ND STREET, NEW YORK	16	2	F	ENGLISH	NY000000000207..	0.286
JANE BUSHEY	Non-Voter	145 EAST 15TH STREET, NEW YORK	16P	2	F	ENGLISH	NY000000000381..	0.011
JANE CAFFERY	Non-Voter	264 EAST 7TH STREET, NEW YORK	1	2	F	ENGLISH	NY000000000533..	0.006
JANE CAFFREY	Non-Voter	264 EAST 7TH STREET, NEW YORK	1	2	F	ENGLISH	NY000000000532..	0.011
JANE CAMPBELL	Voter	201 EAST 17TH STREET, NEW YORK	15E	2	F	CELTIC	NY000000000375..	0.595
JANE CARLTON	Non-Voter	537 EAST 6TH STREET, NEW YORK	5	2	F	ENGLISH	NY000000000532..	0.123
JANE CHAPLINE	Non-Voter	145 4TH AVENUE, NEW YORK	7H	2	F	ENGLISH	NY000000000375..	0.252
JANE CHEUNG	Voter	612 EAST 14TH STREET, NEW YORK	8E	2	F	EAST ASIAN & PACIFIC	NY000000000378..	0.803