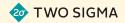


# Transforming Open Data into Insights

How Data Clinic Uses Open Data to Support Mission-Driven Organizations

Erin Stein || @tsdataclinic

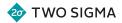




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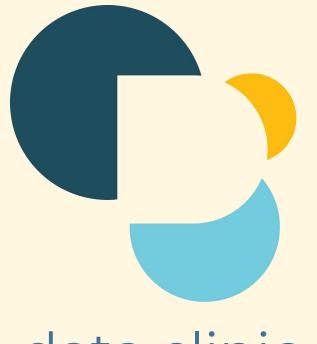






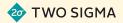






# data clinic

- Pro bono data science and engineering support
- Partner with nonprofits, government agencies, and academic institutions
- Volunteer teams staffed by Two Sigma employees
- Self-driven research and tooling to contribute to the data-for-good movement





#### How we work



engagement + team



research + development



results + impact





#### Data science projects

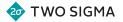






Can we match participants to training programs for maximize success? Can we detect water leaks & meter malfunctions based on a customer's previous usage?

Can we identify why some projects are more likely to be funded than others?





#### Common threads

- → Established organizations
- → A lot of data in-house
- Research questions that could be answered by in-house data

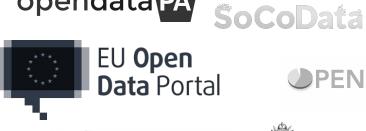






## Why use open data?

- It exists!  $\rightarrow$
- Open data is diverse  $\rightarrow$
- Varied applications/use  $\rightarrow$ cases
  - Build business case for data strategy
  - Advance research



opendata PA















data.world

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## Why use open data?

Build a business case for data strategy



Finding the ways that work

What predicts future oil and gas industry violations?

#### Advance research



#### INSTITUTE OF JUSTICE

Can we provide insight into the national landscape of open 911 call data?





## Building a business case for a data strategy

Build a business case for data strategy



Finding the ways that work

What predicts future oil and gas industry violations?



 Past violations + inspection frequency were highly predictive of future violations

#### $\rightarrow$ Resulted in:

- Culture shift at EDF
- Shared, inter-organizational research strategy



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## Advancing research

- Engaging in research to better understand 911 calls and police enforcement
- No nationally standardized data exists on 911 calls
  - Difficult to understand call volumes, what police are responding to, etc.
- → Initial analysis on Seattle, New Orleans, Charleston, Dallas, and Detroit
  - Develop a pipeline to acquire, clean and standardize open 911 call data

## Advance research Vera INSTITUTE OF JUSTICE Can we provide insight into the national landscape of open 911 call data?











#### Nonexistent and unstructured data



Finding the ways that work

**TWO SIGMA** 

Only ONE of the two states with open data on oil and gas inspections had usable data!





#### Inconsistencies across sources

City	CFS Code	Call Type	Disposition	Lat-Long	Priority	Year Range	Beat/ District
Charleston	Yes	No	Yes	Yes	Νο	'15 - '17	No
Dallas	Yes	No	Yes	Yes	Yes	'05 - '19	Yes
Detroit	Yes	Yes	No	Yes	Yes	'17 - '18	Yes
New Orleans	Yes	Yes	Yes	Yes	Yes	'11-'19	Yes
Seattle	Yes	Yes	Yes	Νο	Yes	'09 - '19	Yes

#### Advance research



#### INSTITUTE OF JUSTICE

While all 5 cities had open 911 data, variables of interest and time spans were inconsistent!



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## Categorical minutiae

Advance research



#### INSTITUTE OF JUSTICE

Categories in the data didn't fit Vera's needs—they were either much too broad or excessively detailed! • 24 broad categories

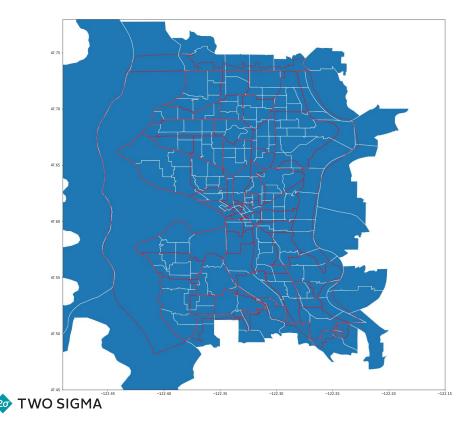
- Top 6 CFS Categories Complaints/Environmental Conditions Statuses Accidents/Traffic Safety Suspicion Assist the Public Alarms
- Each category can contain upwards of 100 different CFS codes for any given city

# Complaints/Environmental Conditions DISTURBANCE, MISCELLANEOUS/OTHER --MISCHIEF OR NUISANCE - GENERAL HAZ - POTENTIAL THRT TO PHYS SAFETY (NO HAZMAT) NOISE - DIST, GENERAL (CONST, RESID, BALL PLAY) LOST PROPERTY VICIOUS ANIMAL FIREWORKS - NUISANCE (NO HAZARD) QUALITY OF LIFE ISSUE --ANIMAL COMPLAINT - NOISE,STRAY,BITE HOMELESS SQUATTER DISTURBANCE





#### Geospatial inconsistencies



#### Advance research

#### Vera INSTITUTE OF JUSTICE

## Geolocation data varied across datasets and cities!



## Open data is HARD



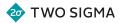
Finding the ways that work

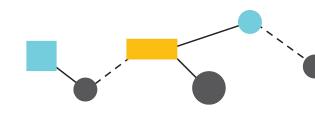


**INSTITUTE OF JUSTICE** 

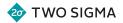
- → Open data is incomplete
- → Open data is messy
  - A lot of free-form text fields
  - Lack of standards in data entry
  - Changing variable names over time
- Original purpose of data collection may not match purpose of the research
- → Just because it's open, doesn't mean it's accessible







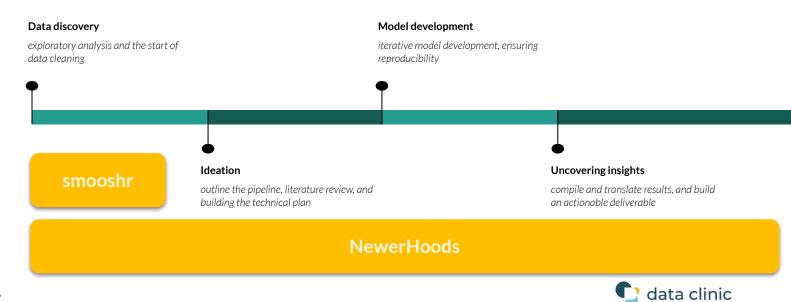
## a little bit of tooling could go a long way





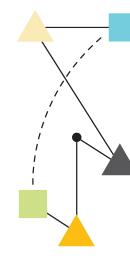
#### Data science pipeline

#### → Developing open source tools throughout the data science pipeline



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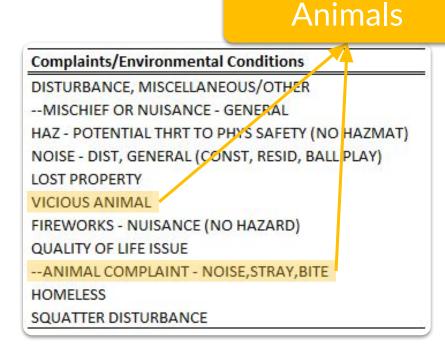
#### smooshr

#### Facilitating entity consolidation of messy data



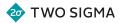


## Creating meaningful variables and taxonomies



- → Understand and join non-uniform, messy text data
  - Create appropriate aggregations
  - Consolidate columns across years or sources that reference same variable
  - Build standard taxonomy within consolidated columns
- Building a tool to facilitate this process through:
  - A user-friendly UI
  - ML approaches to variable category suggestions

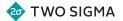




## smooshr || 1. create a project

- → Projects organize all work
  - They contain datasets
  - <u>And</u> the taxonomies you create for them





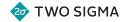


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## smooshr || 2. load in datasets

- Datasets can be loaded from 3 different sources
  - local files
  - urls
  - directly from Socrata open data portals
- Currently we only support tabular data but aim to expand in future

file	url	<u>open data portal</u>
nyc reach members nyc wi-fi hotspot lo nyc service: volunt nyc council constitu nyc school meals in nyc parks monume nyc zoning tax lot o nyc women's resou cash assistance rec nyc health + hospit nyc city hall library 2012 sat results	munity gardens [7] information [7] tions [7] aset [7] s patient care locations - 20 [7] ations [7] er opportunities [7] ent services [7] ome levels [7] s [7] tabase [7] e network database [7] ients in nyc [7] s patient_satisfaction score	





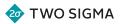
## smooshr || 3. group and rename columns

- Columns from different datasets are often measuring similar things in different circumstances
  - Ex: 911 call reasons across years
- → smoosher lets you collapse these columns into a new column and generate taxonomies for the combined dataset

ooshr	311 Complaints in New York and Chicago
	Datasets Add Dataset
	nola_calls_for_service_2017.csv nola_calls_for_service_2018.csv
	noia_calis_tor_service_2017.csv noia_calis_tor_service_2018.csv
	Columns Merge 2 columns
	InitialTypeText 🗗 166 Disposition 🗗 9
	initialtypetext   nola_calls_for_service_2017.csv disposition   nola_calls_for_service_2017.csv
	work on mappings work on mappings
	InitialTypeText 2 170 DispositionText 2 9
	initialtypetext   nola_calls_for_service_2018.csv dispositiontext   nola_calls_for_service_2018.csv
	work on mappings work on mappings
	Export Mappings (sw) Export Mappings (skon) Export Python code Export Data
<	

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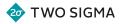
data clinic



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ooshr	311 Complaints in New York and Chicago
	Catasets Add Dataset
	nola calls for service 2017.csv nola calls for service 2018.csv
	nora_caris_tor_service_z017.csv nora_caris_tor_service_2016.csv
	II Columns
	Disposition 🗗 9 Disposition Text 🗗 9
	disposition   nola_calls_for_service_2017.csv dispositiontext   nola_calls_for_service_2018.csv work on mappings
	InitialTypeText 🖻 336
	initialtypetext   nola_calls_for_service_2017.csv initialtypetext   nola_calls_for_service_2018.csv
	work on mappings
	4 Actions
	Export Mappings (csv) Export Mappings (json) Export Python code Export Data
<	



data clinic

#### smooshr || 4. create taxonomies for each column

- Search for unique categories in the combined columns
  - Group multiple entries into new taxonomies
    - New taxonomy can be renamed
- smooshr sends individual words that make up an entry to a server to get word embeddings
  - Suggests other entries that might belong to the current taxonomy

ſ	complaint other		1 (	area check		burglar alarm	silent
	136290 occurances			71845 occurances		59402 occurance	
	disturbance (other) 52899 occurances			auto accident 38518 occurances		warr stop wit 36330 occurance	
Ī	suspicious person 34956 occurances		ÌÌ	return for additional info 29759 occurances	T Ì	business chec 29384 occurance	
	theft 26600 occurances		ÌÌ	domestic disturbance 18068 occurances	T Ì	municipal att 15905 occurance	
	hit & run 15848 occurances		i	fight 13044 occurances	T Ì	auto theft 12071 occurance	15
Ī	simple battery 10959 occurances		ii	directed patrol 10236 occurances	Ì	incident requ agency 10179 occurance	ested by another
	auto accident with in 9505 occurances	njury		simple criminal damage 9233 occurances		fugitive attac 8937 occurances	
1 / 182	entries   89699 / 904987 rd	ows			New	Mapping 0 Add to	Mapping Map Remaining
MERGEI traffic in	D GROUPS	TRAFFIC INCID	ENT 🖻		Suggestions by	: text / meaning	
trarrie in	÷	traffic incident	8		<ul> <li>traffic congest</li> </ul>		police vehicle accident
					traffic attachm	ent 🗸 🗙	directed traffic enforcement
					auto accident p vehicle	police 🗸 🗙	auto accident fatality
						sted by	auto accident city vehicle





#### smooshr || 4. create taxonomies for each column

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WO SIGMA

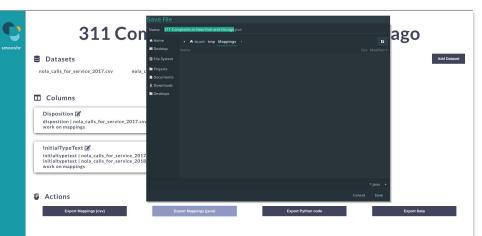
 Suggests other entries that might belong to the current taxonomy

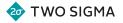
	by: Occurances •		Q the					×		
(	complaint ot 136290 occurar				<b>isturbance (other)</b> 2899 occurances			eft from ex 01 occurances		
(	bicycle theft				neft from exterior of vehi	cle	1			
11/1	182 entries   146184	4 / <b>904987</b> rows					New Mappin	g 0 Add to	o Mapping Map Remain	ing To Other
MERG		2 THE	FT 🗭						o Mapping Map Remaini	ing To Other
			FT 🗹 des	۵	theft by embezzlement	⊗.	Suggestions by: text		o Mapping Map Remain bicycle theft	
MERG traffic		2 THEI Inclusion theft	FT 🗹 des	0	theft by embezzlement auto theft	8	Suggestions by: text			00
MERG traffic		2 THEI Inclust theft	FT 🗭	0		8	Suggestions by: text simple burglary domestic		bicycle theft aggravated burglar theft from exterior	0 ( v 0 (
MERG traffic		2 THE Inclu- theft theft busin	FT 🗹 des by fraud	000000000000000000000000000000000000000	auto theft	8	Suggestions by: text simple burglary domestic residence burglary		bicycle theft aggravated burglar	0 ( v 0 (



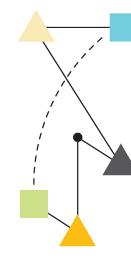
## smooshr || 5. export the results

- → Results / mappings can be exported
  - csv file (in development)
  - JSON document
  - Python code snippet
    - Can be applied to the files in an ETL workflow
    - The transformed data!









#### NewerHoods

#### uncovering patterns in challenging geospatial data





#### Neighborhoods are newsworthy

NYC AFFORDABLE HOUSING NEWS

By Ameena Walker | Oct 2, 2018, 4:18pm EDT

SHARE

neighborhoods

See the NYC neighborhoods where

#### Long Island City — future home to Amazon HQ — is one of NYC's hottest new spots for young people

Laura Begley Bloom, Special to CNBC | 10:30 AM ET Sat, 17 Nov 2018

# Report Reveals NYC Neighborhoods with Highest Asthma Rates

By: **Rob Senior** February 5, 2019

Share: f in У 8

displacement is a growing threat This interactive map illustrates the various factors that contribute to displacement across various Intral Brooklyn. Bronx notorious for

#### New York City's Biggest 'Food Swamps'

By Lea Ceasrine | May 21, 2018

RECOMMEND 🔰 TWEET 🖾 EMAIL 🖨 PRINT 📀 MORE

website indicates the Brownsville section has the ity.

lize.city comes on the heels of the Asthma Free on January 19, and aims to protect tenants from paches, mice, and rats.

## What is a neighborhood?

Social common perceptions	<ul> <li>No clear definition</li> <li>Varies from person to person</li> <li>Eg: "hip" neighborhoods in Brooklyn</li> </ul>
Administrative who is served	<ul> <li>Defined specifically to serve the respective organization</li> <li>Optimized based on organizational costs</li> <li>Static definitions</li> <li>Eg: police precincts or ZIP codes</li> </ul>
Statistical data collection	<ul> <li>Defined to capture areas with a specific population count for data collection &amp; organization</li> <li>Updated approximately every 10 years</li> <li>Eg: US Census block groups or tracts</li> </ul>

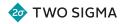




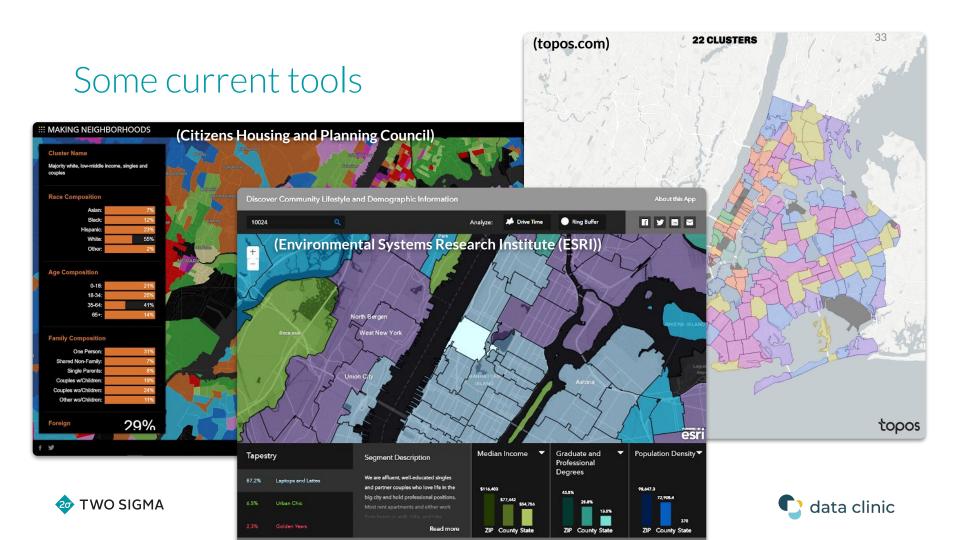
#### Why do we care?

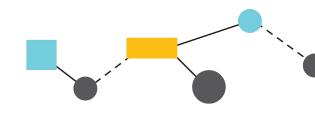




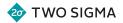


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## An open, flexible, and dynamic tool





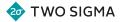
## The approach

**Open Data** 

Local Attributes

#### Clustering

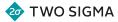
Gather information on a variety of dimensions from NYC Open Data Extract multiple different attributes for every census tract from these data sets Use Machine Learning techniques to find homogenous areas based on chosen characteristics





#### What is a census tract?

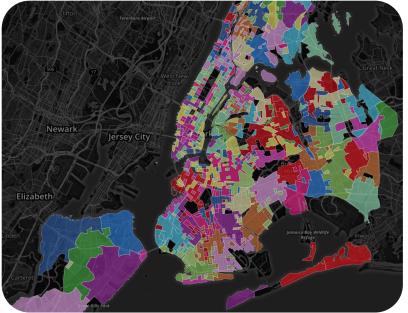






## Traditional clustering methods fail

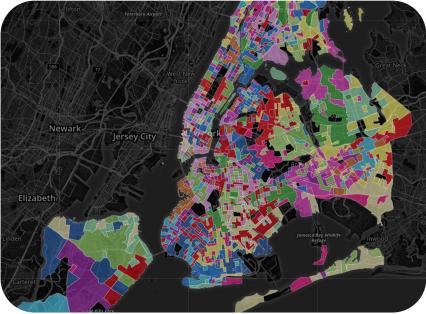
k-means clustering



Scaled features: Mean & sd of price per sq. footage, lat & lon of census tract (k = 100)

💩 TWO SIGMA

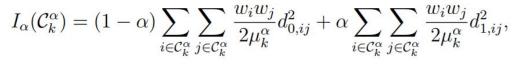
k-means clustering

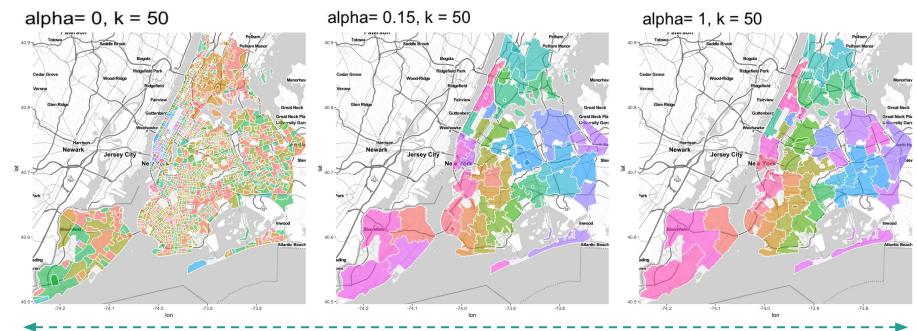


Scaled features: Mean & sd of price per sq. footage, violation rate, noise complaints, lat & lon of census tract (k = 100)



## ClustGeo in action





Geographic space: tract contiguity



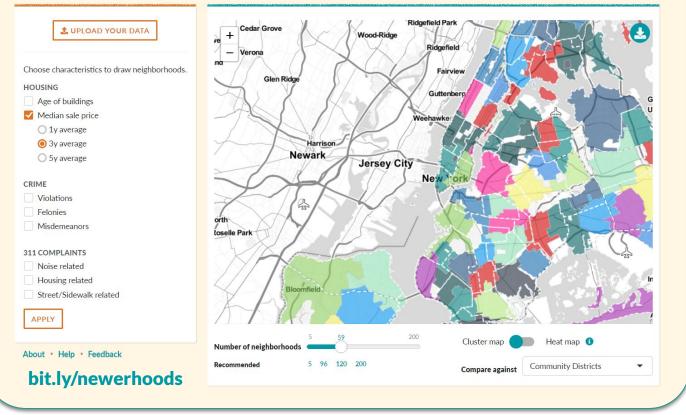
Feature space: mean & sd of price/sq. ft

💠 TWO SIGMA

#### NewerHoods

FROM TWO SIGMA DATA CLINIC

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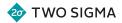






## Applications

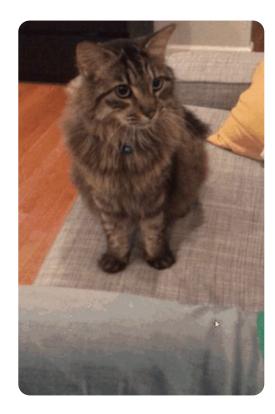
- → Aid social-science research
  - Local/neighborhood effects important in predicting social and economic outcomes
- → Civic tech
  - Analyzing changing boundaries over time could help predict things such as gentrification and aid city planning
- → Individual use
  - Neighborhood reports for community organizers





## Summary

- → Pro bono data science rules!
- → Use open data
  - Fills data gaps
  - Low/no-cost proof of concept
  - Expand current reach of research
- → Build tools for repetitive tasks
  - Helps you AND helps others







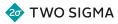
#### Contribute

#### → Connect on GitHub

- Take part in tool development
- Submit issues
- → Email us
  - Provide feedback
  - Refer potential use cases
- → Visit our website
  - Follow our progress on projects and tooling









Erin Stein dataclinic.twosigma.com @tsdataclinic <u>dataclinic@twosigma.com</u>

