Using Machine Learning to Target Assistance: Identifying Tenants at Risk of Landlord Harassment

Rebecca Johnson [1,2], Teng Ye [3], Samantha Fu [4], Jerica Copeny [5], Bridgit Donnelly [6], Alex Freeman [7], Mirian Lima [8], Joe Walsh [8], and Rayid Ghani [8]

[1] Office of Population Research, Princeton University, [2]Department of Sociology, Princeton University

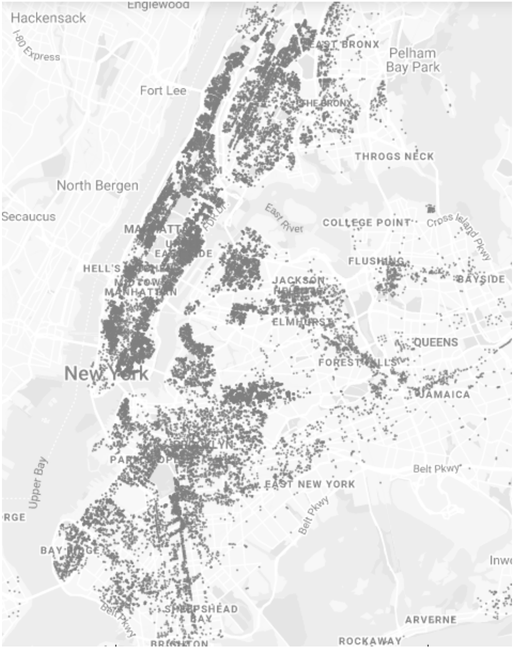
[3]University of Michigan, [4]Evansville Public Library, [5]London School of Economics,

[6]Mayor's Public Engagement Unit (former), [7]Mayor's Public Engagement Unit,

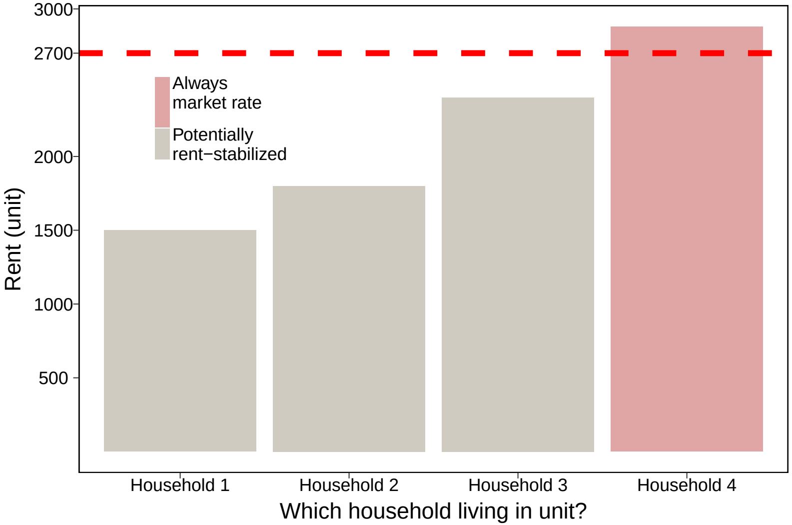
[8]Center for Data Science and Public Policy

PAA: April 11th, 2019

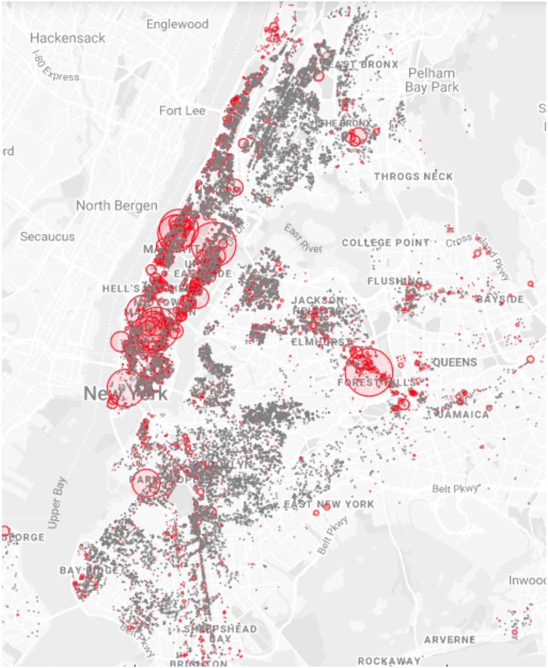
Rent stabilization is an important policy lever against housing instability...



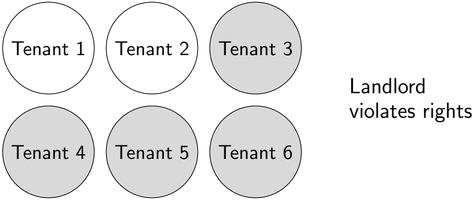
...But some landlords exploit legal loopholes to convert rent-stabilized apartments to market-rate ones



Contributing to conversion of over 38,000 rent-stabilized apartments to market-rate ones (2007-2015)



Reactive rights enforcement can lead to biases in which tenants receive help to combat landlord harassment



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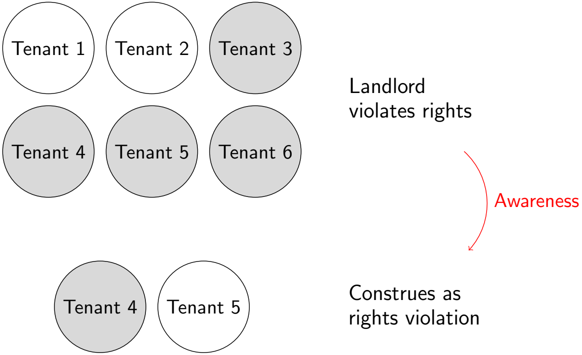
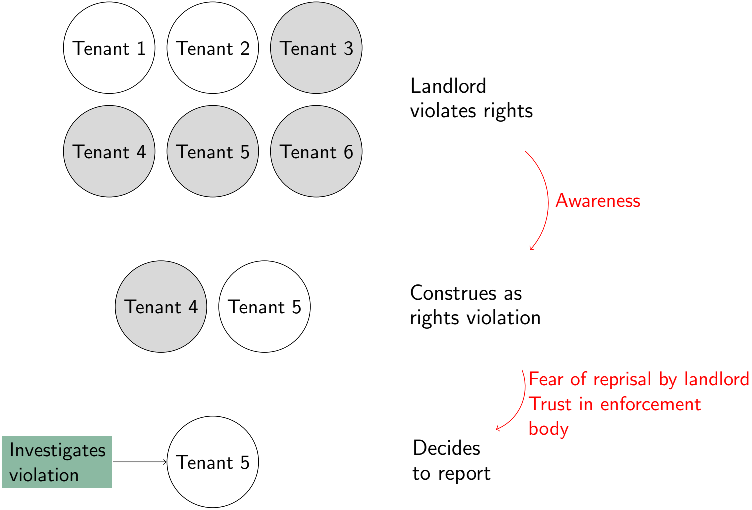


Reactive rights enforcement can lead to biases in which tenants receive help to combat landlord harassment



Potential way to ameliorate biases: *proactive* rights enforcement

When it comes to protecting tenants and affordable housing, we don't wait for a 311 call to come in.

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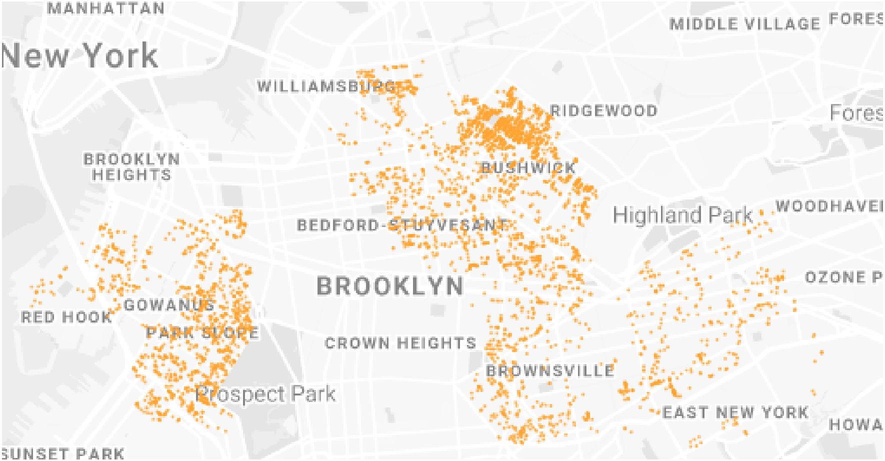
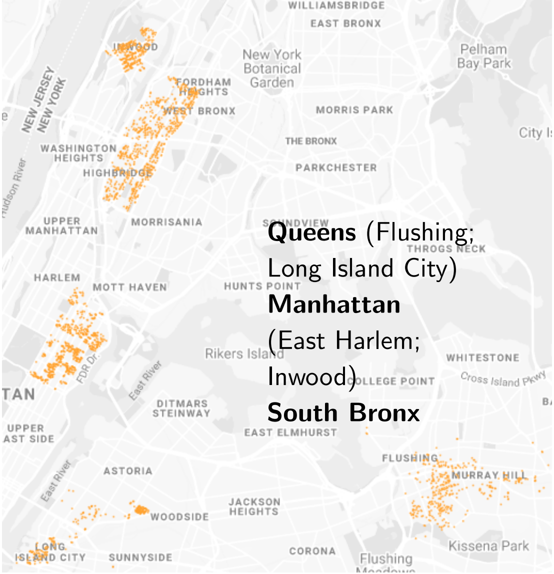
When it comes to protecting tenants and affordable housing, we don't wait for a 311 call to come in.

We have teams [Tenant Support Unit (TSU)] knocking on doors in fast-changing neighborhoods to solve problems then and there. (Mayor Bill de Blasio, 2016)

How should the Tenant Support Unit prioritize visits among ~ 6500 buildings containing $\sim 142{,}000$ residential units?

Brooklyn (Bushwick; Gowanus; East New York)





Queens (Flushing; Long Island City)

Manhattan (East Harlem; Inwood)

South Bronx

Have thus far gone block by block generating monthly lists for proactive engagement

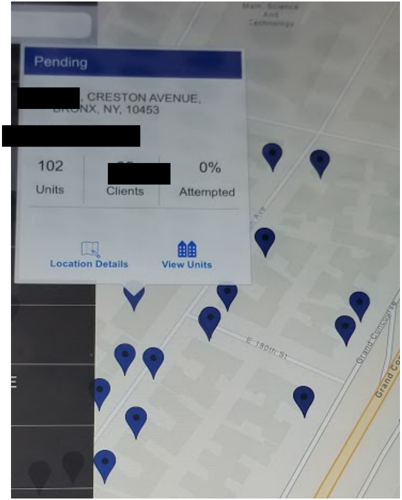
Outreach list: Bushwick Sub-Team
June 2016

Address	*Borough*	Sub-*team*
a5243	Brooklyn	Bushwick
a2110	Brooklyn	Bushwick
⋮		
a0052	Brooklyn	Bushwick

Outreach list: Flushing Sub-Team
June 2016

Address	*Borough*	Sub-*team*
a0031	Queens	Flushing
a1947	Queens	Flushing
⋮		
a6042	Queens	Flushing

Using large-scale data to improve prioritization



k: knocks; o: door opens; c: harassment cases

ID	Date	k	o	c
a1	06-01-2016	18	5	1
a1	06-02-2016	0	NA	NA
a2	06-01-2016	20	7	0
a2	06-02-2016	30	10	2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
a_n	06-01-2016	10	0	0

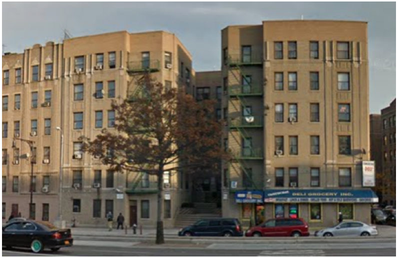
Using large-scale data to improve prioritization

Building A in Bronx:

Total knocks ($\sum_{m=1}^{32} k_{bm}$): 75

Total opens ($\sum_{m=1}^{32} o_{bm}$): 52

Total cases ($\sum_{m=1}^{32} c_{bm}$): 21



Building B in Queens:

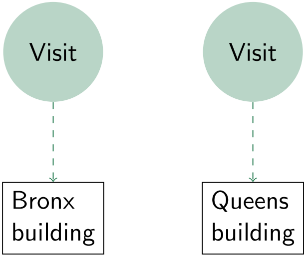
Total knocks: 523

Total opens: 115

Total cases: 0

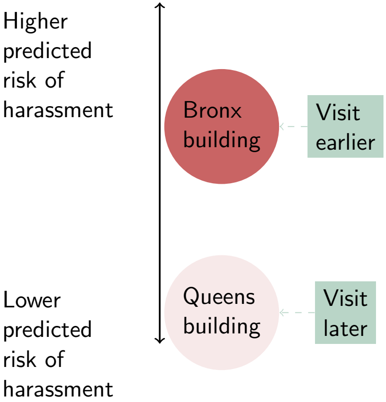
Applying machine learning to that large-scale data to improve prioritization

Current outreach:

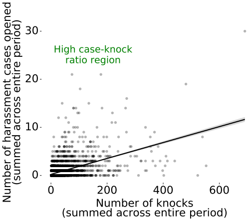


vs.

Machine learning (ML)-guided prioritization:



Steps in ML-guided prioritization: (1) define label



1. Labels to model (for building b in month m):

- Any new case in next month
- New cases/units $>$ threshold

Steps in ML-guided prioritization: (1) define label; (2) choose features

1. Define label

2. Choose features:
Internal (e.g., "which specialists visit?")
Building (e.g., "who is landlord?"(use fuzzy string matching to match
BAINBRIDGE CLASTER AS;
BAINBRIDGE CLUSTER AS;
BAINRIDGE CLUSTER ASS))
Violations (e.g., "how many violations found by code enforcement agency?")
Neighborhoods (ACS tract) (e.g., "what's the demographic composition? When are people home?")

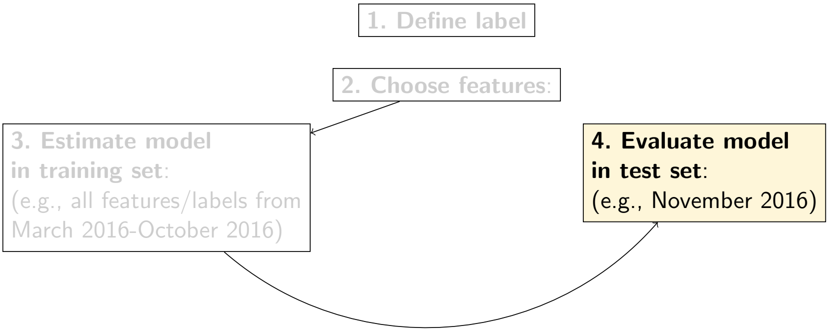
Steps in ML-guided prioritization: (1) define label; (2) choose features; (3) split data temporally and estimate model in training set

1. Define label

2. Choose features:

3. Estimate model in training set:
(e.g., all features/labels from March 2016-October 2016)

Steps in ML-guided prioritization: (1) define label; (2) choose features; (3) split data temporally and estimate model in training set, (4) evaluate performance in test set

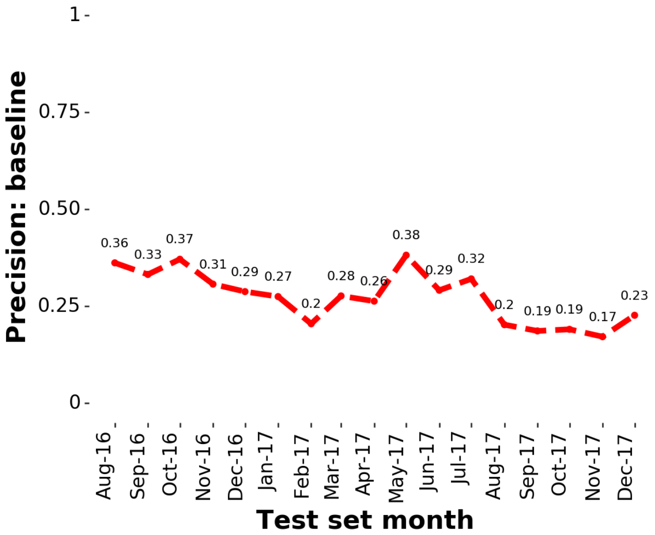


Steps in ML-guided prioritization: (1) define label; (2) choose features, (3) split data temporally and estimate model in training set, (4) evaluate performance in test set

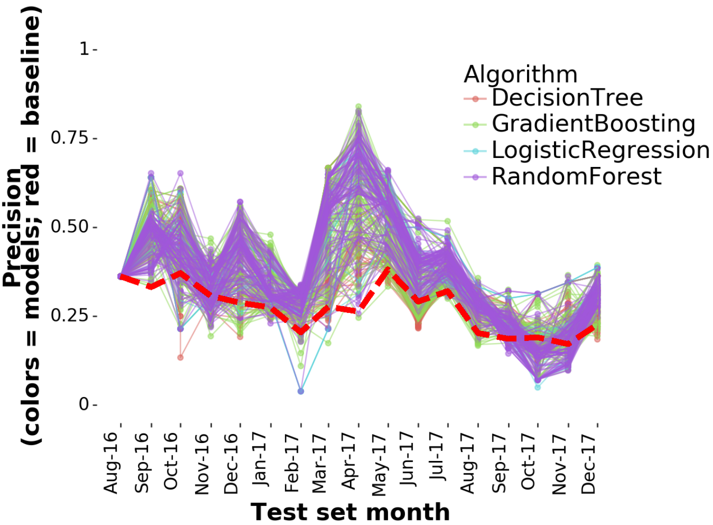
ID	Y **True label**	Score	$\hat{Y}$ **Pred. label**	# of units	# of cases
a5	1	0.8	**1**	153	34
a7	NA	0.79	**1**	23	NA
a8	0	0.65	**1**	77	0
Total units				*253*	
a4	NA	0.46	**0**	100	NA
a1	0	0.45	**0**	10	0

$$\frac{\#\text{ true positive labels below capacity threshold}}{\#\text{ of labels below capacity threshold}} = \frac{1}{2}$$

What we want to outperform: TSU's existing prioritization

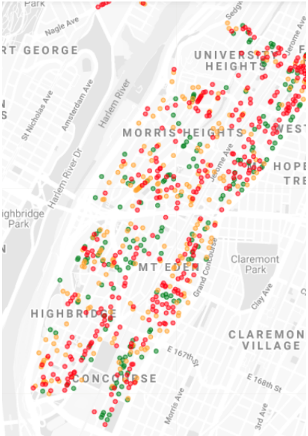


Nearly all models outperform that existing prioritization



Focusing on best-performing model (gradient boosting with 10,000 estimators)

Risk tertiles in South Bronx (any case):



Staying at their same capacity to visit ∼ 60,000 residential units each year, 40-80% increase in performance:

- *Before ML-guided prioritization:* TSU finds ∼ **1800 cases** of landlord harassment

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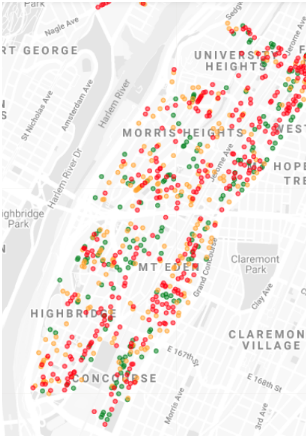

Staying at their same capacity to visit ∼ 60,000 residential units each year, 40-80% increase in performance:

- *Before ML-guided prioritization:* TSU finds ∼ **1800 cases** of landlord harassment
- *Using ML-guided prioritization:* TSU finds ∼ **2500-3300 cases** of landlord harassment

Does this increase in efficiency come at the expense of equity?

- Critics of social service organizations using machine learning to prioritize argues that increased efficiency may come at the expense of fairness (e.g., O'Neil, 2017; Eubanks, 2018; Bakalar and Zevenbergen, 2017; Bakalar and Zevenbergen, 2017)

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- Suggests that, in addition to examining *aggregate* improvements, should ensure that buildings flagged as highest-risk align with substantive notions of need and vulnerability

Evaluating fairness: ability to capture different forms of vulnerability to harassment

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- Theory (e.g., Sharkey, 2013; Hwang and Sampson, 2014; Desmond, 2016) highlights different potential pathways into high harassment risk:

Buildings in 20 target zip codes with at least 1 rent-stabilized unit

Type of neighborhood: "gentrifying" (poverty + large increase in median income (2000-2010))

Reason for harassment: strong financial incentives to convert units to market rate

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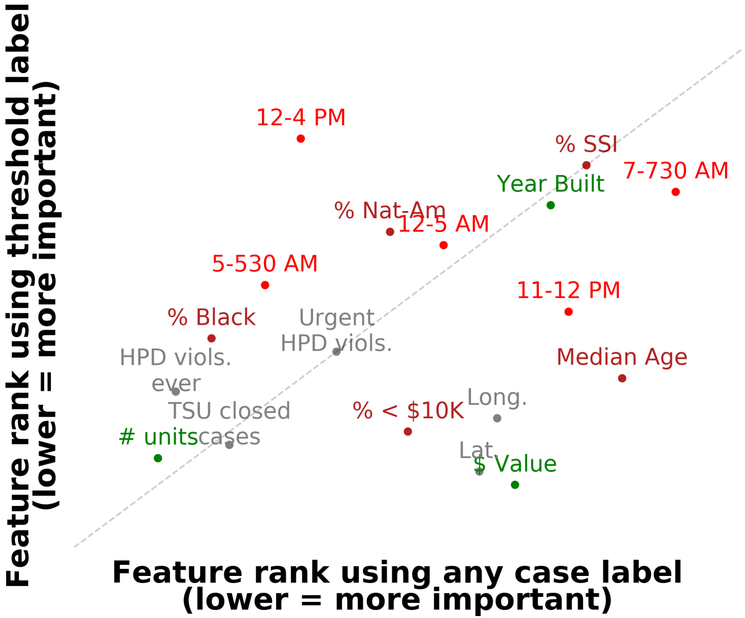
Reason for harassment: strong financial incentives to convert units to market rate

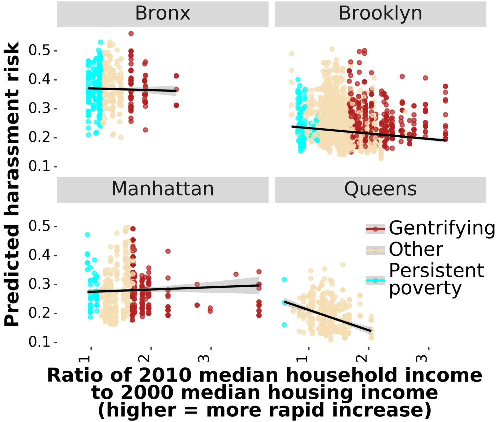
Type of neighborhood: "persistent poverty" (poverty + little increase in median income (2000-2010)

Reason for harassment: persistent landlord-tenant power asymmetries


Feature rank using threshold label
(lower = more important)
Feature rank using any case label
(lower = more important)


12-4 PM
% SSI
7-730 AM
Year Built
% Nat-Am
12-5 AM
5-530 AM
11-12 PM
% Black
Urgent
HPD viols.
HPD viols.
ever
Median Age
Long.
TSU closed
cases
% < $10K
# units
Lat.
$ Value
Feature rank using threshold label
(lower = more important)
Feature rank using any case label
(lower = more important)

High predicted harassment risk in both gentrifying and persistent poverty neighborhoods



Use LTDB (Logan et al., 2012); similar to Ellen and Torrats-Espinosa (2018), use large change in median household income as a measure of gentrification

Discussion and next steps

1. **Policy:** before deploying, field trial to generate exogenous variation in knocks (non-random missingness in building's harassment label, which is only observed in month m for buildings they visited and where at least one tenant opened the door)
   - Selective labels problem: Lakkaraju et al. (2017); Casey et al. (2018); Knox, Lowe, Mummolo (2019)
2. **Theory:**
   - More direct comparison to predicted risk if used reactive rights enforcement (e.g., go to high 311 call-volume areas)
   - Landlords
   - Zip code discontinuities and tenant outcomes

Thanks!

http://scholar.princeton.edu/rebeccajohnson/

raj2@princeton.edu

Appendix

Background: policy levers to increase housing affordability

$$\frac{\text{Monthly rent}}{\text{Monthly income}}$$

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3. Rent stabilization:
Acts on: numerator;
Attaches to: a housing unit

TSU's current method for prioritizing which buildings to visit: expert judgment

Target universe: buildings in
20 target zip codes with
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↓

TSU team lead puts building b on knock list in month m

Labels: details

Throughout: since TSU ranks buildings at the beginning of each month, risk of a *new case* of landlord harassment in the upcoming month

Any case label - any case in the next month:

$$y_{bm} = \begin{cases} 0 & \textit{if } k_{bm} \geq 1, o_{bm} \geq 1, \\ & c_{bm} = 0 \\ 1 & \textit{if } k_{bm} \geq 1, o_{bm} \geq 1, \\ & c_{bm} \geq 1 \\ NA & \text{otherwise} \end{cases}$$

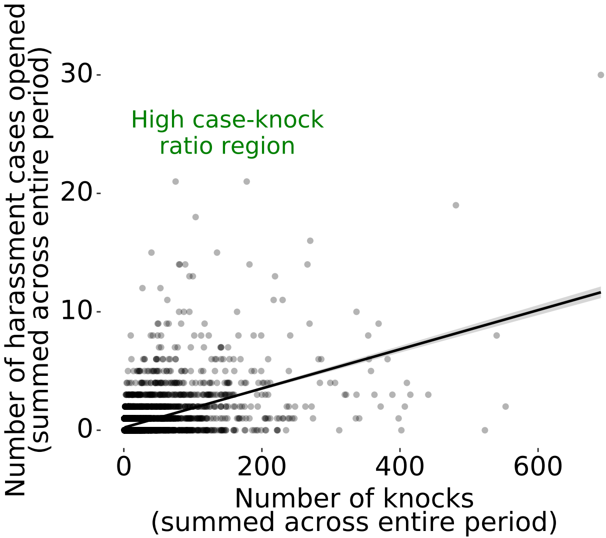
Threshold label- case/units $>$ ratio in next month:

τ = percentile threshold;

$i_b = \#$ of units at building b

$$y_{bm} = \begin{cases} 0 & \textit{if } k_{bm} \geq 1, o_{bm} \geq 1, \\ & \frac{c_{bm}}{i_b} < \tau \\ 1 & \textit{if } k_{bm} \geq 1, o_{bm} \geq 1, \\ & \frac{c_{bm}}{i_b} \geq \tau \\ NA & \text{otherwise} \end{cases}$$

Labels: details



Features: details

Source	Unit of analysis	Example features
Tenant Support Unit	Building	Total cases up to month m; which specialist visits; which zip code
Primary Land Use and Tax Lot (PLUTO)	Building	Landlord (use fuzzy string matching to match BAINBRIDGE CLASTER AS; BAINBRIDGE CLUSTER AS; BAINRIDGE CLUSTER ASS); Building value
HPD, Housing Court, Subsidized Housing (NYC Open data)	Building	Code violations; litigation against landlord
ACS 5-year estimates	Tract	Racial/socioeconomic composition; rent burden; hours work outside home

Total: $\sim$ 400; using 120 for current model; pre-processed using imputation, normalization of continuous features with minimum-maximum scaling, and converting categorical to dummy indicators for levels with $\geq$ buildings

Details on temporal split

ID	Month	Y	HPD viols. (ever)	Tract % Black	...
a1	06-2016	1	0	50	
a5	06-2016	0	20	70	
a8	06-2016	0	5	5	
⋮					
a8	10-2016	0	8	5	

Details on temporal split

ID	Month	Y	HPD viols. (ever)	Tract % Black	...
a1	06-2016	1	0	50	
a5	06-2016	0	20	70	
a8	06-2016	0	5	5	
⋮					
a8	10-2016	0	8	5	
a1	11-2016	NA	5	50	
a2	11-2016	NA	54	70	
a3	11-2016	1	2	15	
⋮					

Step three for learning harassment risk: use machine learning to learn risk as a flexible function of those features

1. For each split, train model j on data from month $= 1 \ldots$ m

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   - Rank all test set buildings by $\hat{y}$
   - Draw capacity threshold τ at half of TSU's observed outreach capacity

Address ID	Score	# of Units	Pred. Label	True Label	# of Cases
a5	0.81	153	1	1	34
a7	0.68	23	1		
a8	0.62	77	1	0	12
Total units				*253*	
a4	0.48	300	0		
a1	0.46	100	0	1	23

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   - Using buildings with observed labels, calculate metric (main: precision at τ):

$$\frac{\#\text{ true positive labels below }\tau}{\#\text{ of labels below }\tau} = \frac{1}{2}$$

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4. Repeat for model $j + 1$

Step four in learning harassment risk: evaluate performance in the held-out test set

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- Using buildings with observed labels, calculate metric (main: precision at capacity threshold):

$$\frac{\#\text{ true positive labels below capacity threshold}}{\#\text{ of labels below capacity threshold}} = \frac{1}{2}$$

Compare $N \sim 800$ models to that expert judgment

DT: Decision Tree; RF: Random Forest; GB: Gradient Boosting; LR: Penalized Logistic Regression (Ridge and Lasso)

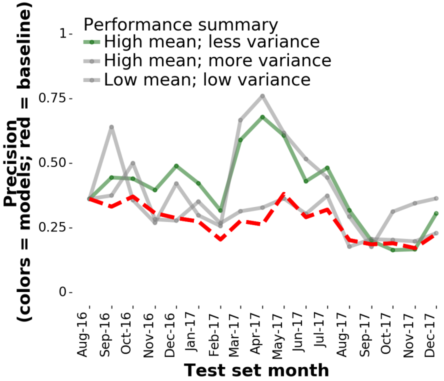
```
large_grid = {
    'RF':{'n_estimators': [1,10,100,1000,10000], 'max_depth': [1,5,10,20,50,100],
    'max_features': ['sqrt','log2'],'min_samples_split': [2,5,10], 'n_jobs': [-1]},

    'LR': { 'penalty': ['l1','l2'], 'C': [0.00001,0.0001,0.001,0.01,0.1,1,10]},

    'GB': {'n_estimators': [1,10,100,1000,10000],
    'learning_rate' : [0.001,0.01,0.05,0.1,0.5],
    'subsample' : [0.1,0.5,1.0], 'max_depth': [1,3,5,10,20,50,100]},

    'DT': {'criterion': ['gini', 'entropy'], 'max_depth': [1,5,10,20,50,100],
    'min_samples_split': [2,5,10]},
          }
```

Weighting performance across different test set months



Result: gradient boosting with 10,000 estimators; learning rate of 0.001; split criterion is Friedman mean squared error; average performance ratio of 1.54 means TSU can visit the same number of buildings and find 54 more buildings with any case

Machine learning (ML) and demography/social science

Athey (2017), Molina and Garip (2019), and others discuss what social science contributes to ML and what ML contributes to social science

1. **Predictions**: fairness and variation in predicted risk under different label definitions

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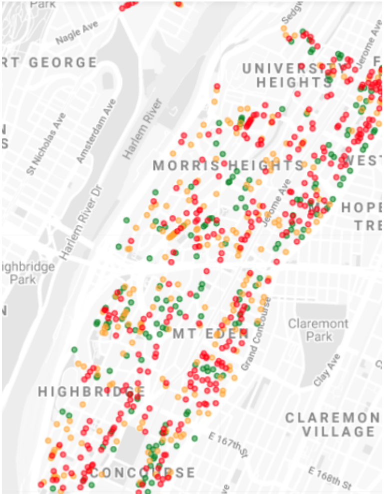
Athey (2017), Molina and Garip (2019), and others discuss what social science contributes to ML and what ML contributes to social science

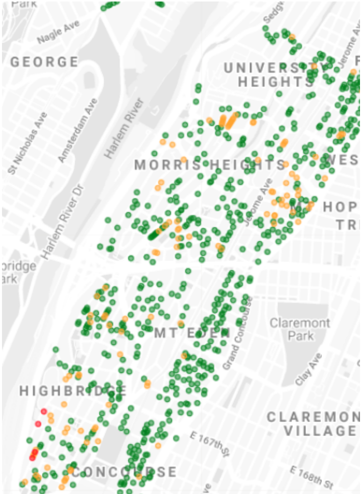
1. **Predictions**: fairness and variation in predicted risk under different label definitions

Risk tertile: area of Bronx under different label definitions (same gradient boosting model + same hyperparameters)

Any case:

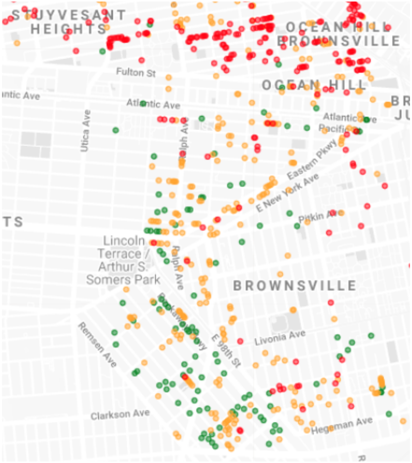


Case per units > threshold:



Risk tertile: area of Brooklyn under each label

Any case:



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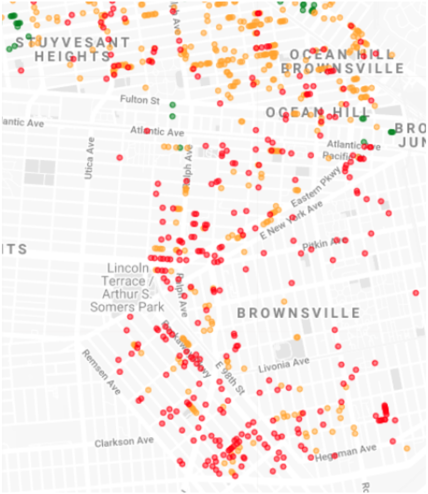

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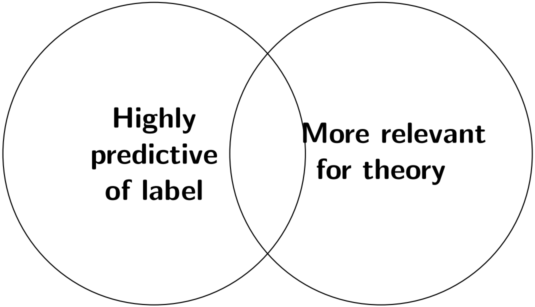
  - Variation in that proportion is relevant

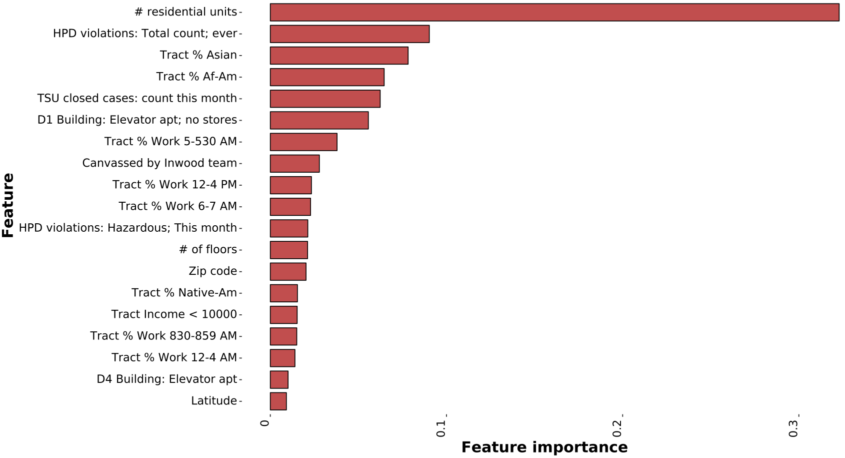
Machine learning (ML) and demography/social science

Athey (2017), Molina and Garip (2019), and others discuss what social science contributes to ML and what ML contributes to social science

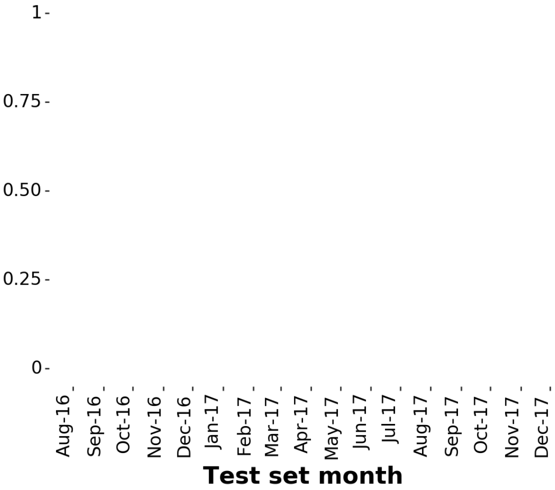
1. **Predictions**: fairness and variation in predicted risk under different label definitions
2. **Feature interpretation:** Goldilocks region:



Largest feature importances: any case label



Step three in learning harassment risk: use training set to estimate risk as flexible function of features



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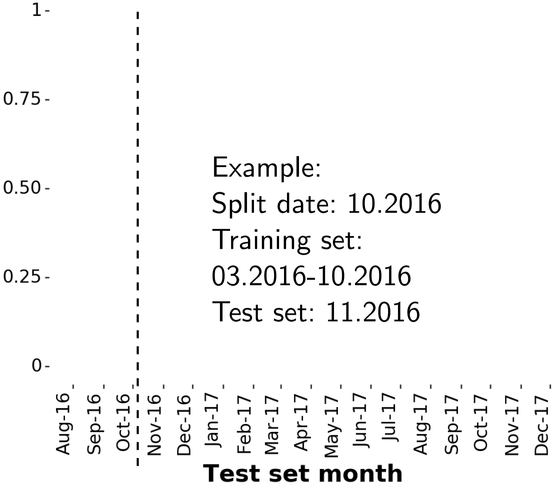

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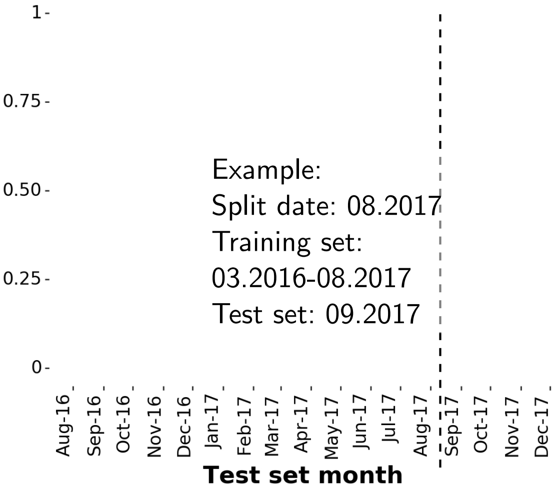
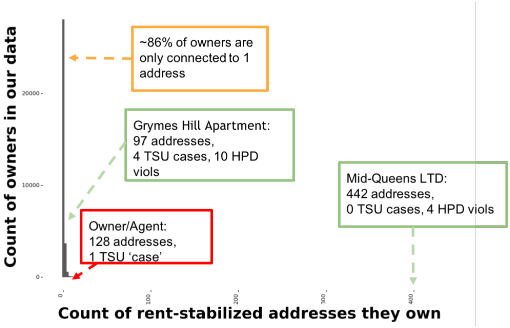


Features: relevant for theory but not highly predictive of label



Despite fuzzy string matching to map multiple spellings to same owner, e.g.:
BAINBRIDGE CLASTER AS
BAINBRIDGE CLUSTER AS
BAINRIDGE CLUSTER ASS

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  - "Gentrifying" neighborhoods: stronger incentives to convert units to market-rate ones
  - "Stuck in place" neighborhoods: landlords take actions like neglect serious repairs or cut off heat less to try to get tenants to move out and more due to power asymmetries/as a way to extract unpaid rent (Desmond, 2016)

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