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

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DS at DC: 10.16.19

Overview

- **Substance:** Background on why NYC agency we partnered with– the Public Engagement Unit (PEU) and their Tenant Support Unit (TSU) within NYC's Mayor De Blasio's – 1) wanted to use machine learning to target outreach efforts to tenants; and 2) viewed these outreach efforts as important in combating housing instability before it reached the point of eviction/homelessness: https://dl.acm.org/citation.cfm?id=3332484

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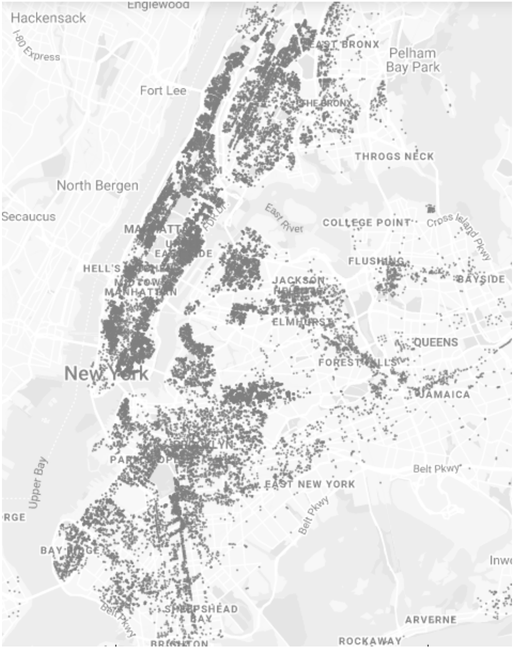
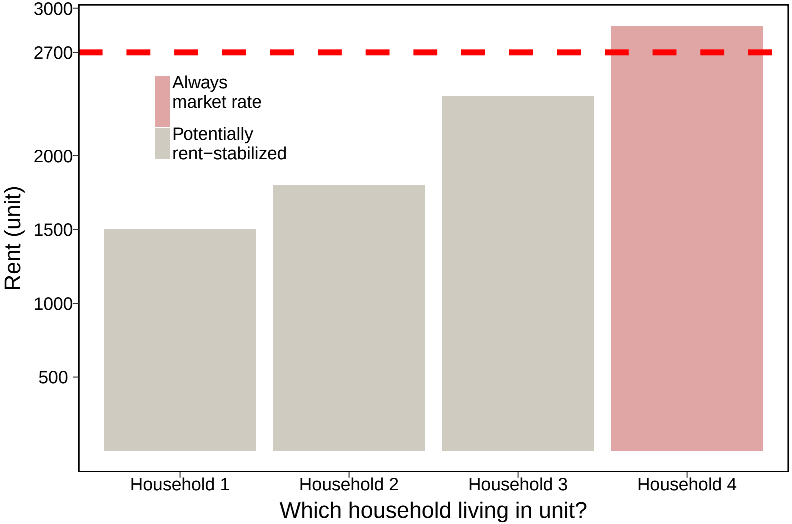
    - **Newer approaches:** predictive models
        - Lab at DC: past projects on housing code violations; rate inspections; future on student absenteeism

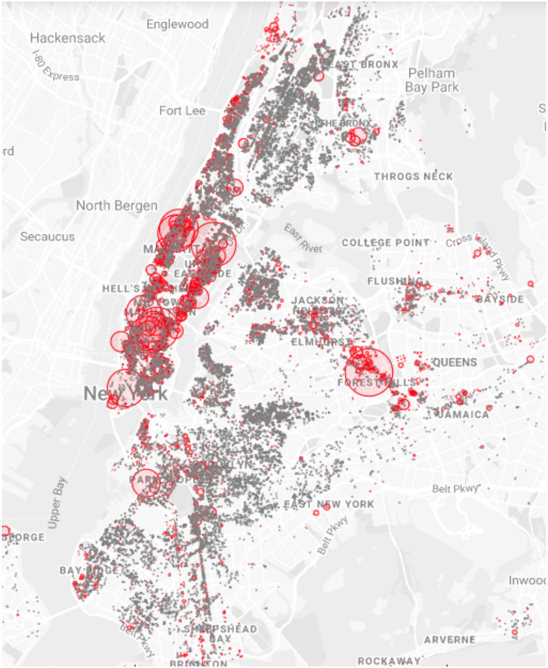
Rent stabilization is an important policy lever against housing instability...



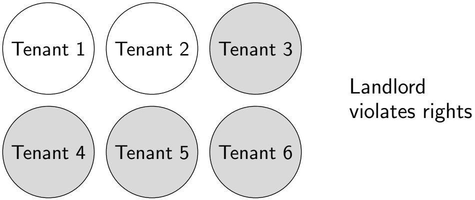
...But some landlords exploit legal loopholes to convert rent-stabilized apartments to market-rate ones



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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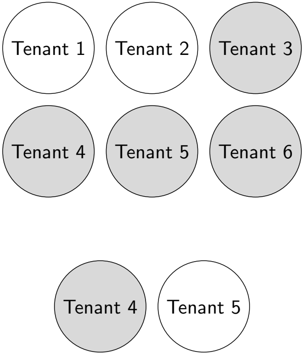
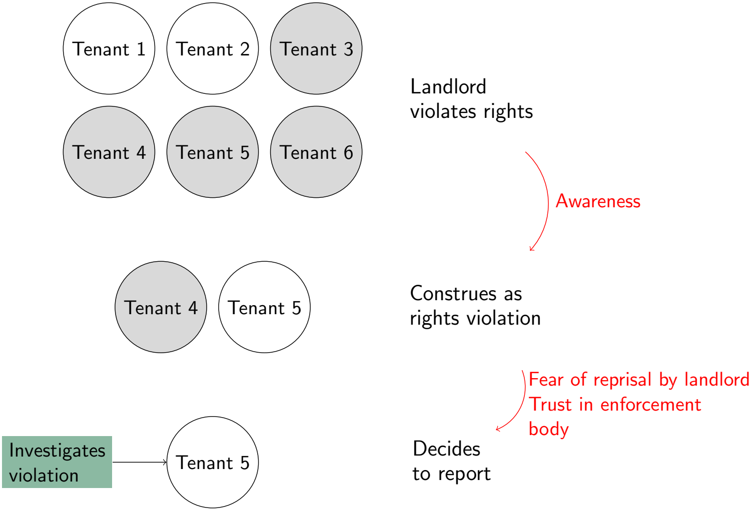


Landlord violates rights

Awareness

Construes as rights violation

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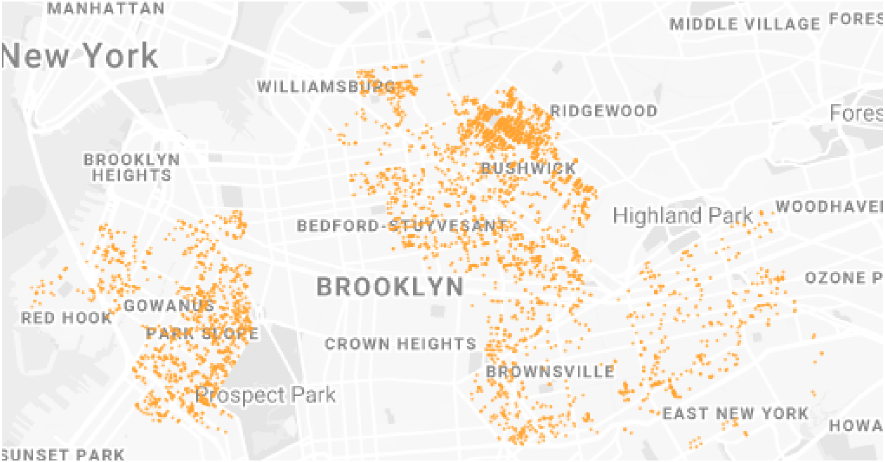
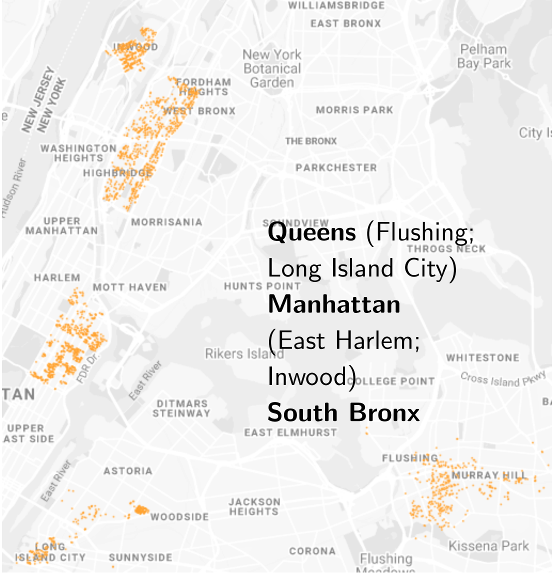
We have teams [Tenant Support Unit (TSU)] knocking on doors in fast-changing neighborhoods to solve problems then and there. (Mayor Bill de Blasio, 2016)

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

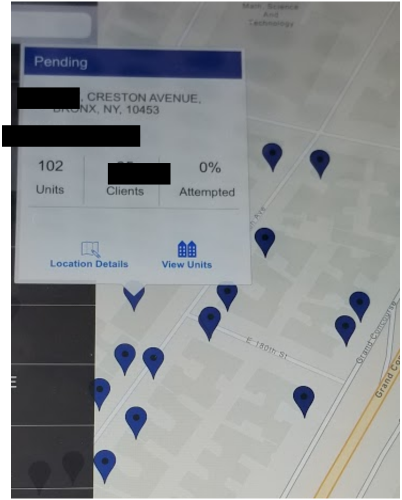
Outreach list: Bushwick Sub-Team
June 2016

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
⋮	⋮	⋮	⋮	⋮
a_n	06-01-2016	10	0	0

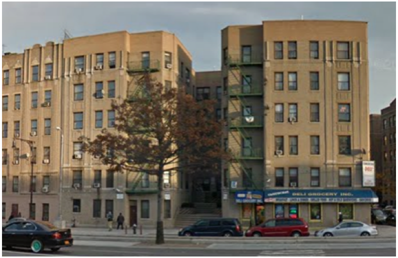
Using large-scale data to improve prioritization

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:

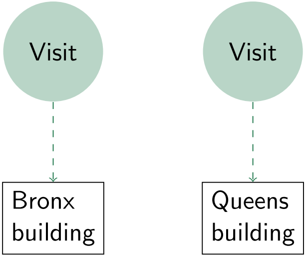
Total knocks: 523

Total opens: 115

Total cases: 0

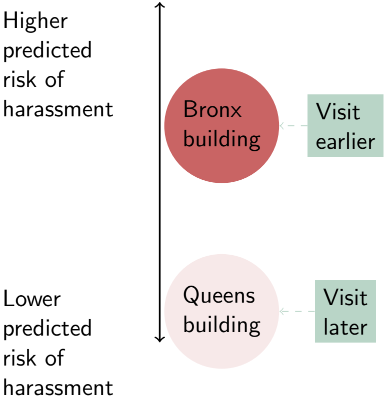
Applying machine learning to that large-scale data to improve prioritization

Current outreach:

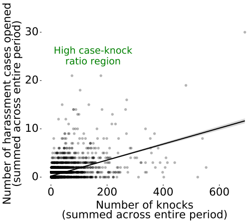


vs.

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?")

Details on features and pre-processing

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: ~ 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

Interfacing with NYC's open data

Goal: interface directly rather than point and click download of a flat file (given daily updates for things like housing code violations): script

```python

## for now, didnt use credentials but later change
client_data = Socrata("data.cityofnewyork.us",
                    creds['nyc_api_getdata']['apikey'],
                    username = creds['nyc_api_getdata']['username'],
                    password = creds['nyc_api_getdata']['password'])
client_metadata = Socrata("data.cityofnewyork.us",
                    creds['nyc_api_getmetadata']['apikey'],
                    username = creds['nyc_api_getmetadata']['username'],
                    password = creds['nyc_api_getmetadata']['password'])


### cleaned version of json ID
jsonid_forget = clean_json(data = opendata_links_valid,
                           dataname = dataname)

### limit parameter - either feeds it
### approximate size if data has unique ID
### or uses the approximate size to get row limit
if int(opendata_links_valid[opendata_links_valid.dataname == dataname]['unique_id']) == 1:
    limit_parameter = generate_limit_parameter(data = opendata_links_valid,
            dataname = dataname, client_metadata = client_metadata)
else:
    limit_parameter = int(opendata_links_valid[opendata_links_valid.dataname == dataname]['size_approx']) + 10000


logger.info("generated lim parameter: " + str(limit_parameter) + " for: " + dataname)


## generate chunks of data to pool and pull from API in parallel
offset_range = list(range(0, limit_parameter, 10000))
print(len(offset_range))
pool = Pool() # Create a multiprocessing Pool; could test with 1 to test sequential version and put time buffer
print('started pool')
df_list = pool.map(getdf_fromapi_onechunk, offset_range)

```

```python
@retry(wait_exponential_multiplier=1000, wait_exponential_max=10000)
def getdf_fromapi_onechunk(offset_start):
    one_get = client_data.get(jsonid_forget, limit = 10000,
                              offset = offset_start) # call
    one_df = pd.DataFrame.from_records(one_get)
    return(one_df)
```

Using SQL for efficiency gains relative to Python

```sql
-- and distkey and sortkey
DROP TABLE IF EXISTS dssg_clean.housinglitig_tomerge;
CREATE TABLE dssg_clean.housinglitig_tomerge
AS

SELECT
            bin_clean
            ,week_start
            ,month_start
            ,count(*) AS housinglitig_count
            ,sum(housinglitig_tenantaction) AS housinglitig_tenantaction_count
            ,sum(housinglitig_heatwater) AS housinglitig_heatwater_count
            ,CASE WHEN count(*) > 0 THEN 1 ELSE 0 END AS housinglitig_any
            ,CASE WHEN sum(housinglitig_tenantaction) > 0 THEN 1 ELSE 0 END AS housinglitig_tenantaction_any
            ,CASE WHEN sum(housinglitig_heatwater) > 0 THEN 1 ELSE 0 END AS housinglitig_heatwater_any
            ,SUM(COUNT(*)) OVER(PARTITION BY bin_clean ORDER BY bin_clean, week_start ASC ROWS UNBOUNDED PRECEDING) AS housingl
FROM
        (SELECT *,
                CASE WHEN casetype LIKE 'Tenant Action%' THEN 1 ELSE 0 END AS housinglitig_tenantaction,
                CASE WHEN casetype LIKE 'Heat%' THEN 1 ELSE 0 END AS housinglitig_heatwater,
                date_trunc('week', date_clean) as week_start,
                date_TRUNC('month', date_clean) AS month_start
         FROM
                -- convert from varchar to date-time format for date-- use the date when DOB query is pushed to open data
                -- convert from integer to varchar for bin
                    (SELECT *,
                        to_date(caseopendate, 'MM--DD-YYYY') as date_clean,
                        bin::varchar(5204) AS bin_clean
                    FROM raw.housingcourt_litigation
                    )  as cleandate
         ) cleandate2

-- aggregate by bin and start of week
GROUP BY bin_clean, week_start, month_start
ORDER BY bin_clean, week_start ASC;
```

Hack-y way to give intuitive variable names for many ACS tract-level features

poverty	B06012_001	poverty status	Total Population In The United States For Whom Poverty Status Is Determined
poverty	B06012_002		Below 100 percent of the poverty level
poverty	B06012_003		100 to 149 percent of the poverty level
poverty	B06012_004		At or above 150 percent of the poverty level
employment	B08007_001	place of work	Total Workers 16 Years And Over

```
## create prefix and suffix columns
df_acs_long['variable_prefix'], df_acs_long['variable_suffix'] = df_acs_long['variable'].str.split('_', 1).str
```

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)

Estimating (and then evaluating) $N \sim 800$ models

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]},
        }
```

Ways we made more automatic

Directory with some snippets

- Used naming conventions for different types of features (e.g., ACS versus HPD violations) so that we could easily create lists that combine different features

```
## iterate over patterns and choose the cols
pattern_list = ['^internal.*', '^internal.*static',
                 '^internal.*count_next.*',
                 '^internal.*any_next.*',
                 '.*cases.*this.*|.*knocks.*this.*|.*opens.*this.*',
                '^hpd.*', '^housinglitig.*',
                '^pluto.*', '^acs_2015.*',
                '^acs_2016.*',
                 '^acs_2015_tract_percent.*',
                 '^acs_2016_tract_percent.*',
                 '^acs_2015_tract_count.*',
                 '^acs_2016_tract_count.*',
                '^subs|^rent.*']

names_list = ['internal_all', 'internal_static',
              'internal_continuous_labels',
              'internal_binary_labels',
              'internal_lagged_labels',
               'hpd', 'housing_litigation',
               'pluto', 'acs_2015_all',
               'acs_2016_all',
              'acs_2015_percent',
              'acs_2016_percent',
              'acs_2015_count',
              'acs_2016_count',
               'misc']
```

Ways we made more automatic

- Created a schema – `results` –that creates a unique identifier for each model run and parses key information

```
def pull_from_eval(alchemy_connection, id_lower = 0, id_upper=900000000, subset_list = False, id_list = '(0)',
                label_topull = 'internal_cases_opened_any_next_month',
                boroughs_fit_topull = 'Bronx_Queens_Staten Island_Brooklyn_Manhattan',
                maxgaptraintest_topull = 40):

    if subset_list == True:

        print('pulling ID list')

        pull_results_info = """
                select * from dssg_results.eval_meta
                where model_id in {id_list}
                and label = '{label_topull}'
                and borough_fit_on = '{boroughs_fit_topull}'
                order by model_id desc;
                """.format(id_list = id_list,
                          label_topull = label_topull,
                          boroughs_fit_topull = boroughs_fit_topull)

                ## pull from database
        df_eval = readquery_todf_postgres(sqlalchemy.text(pull_results_info),
                                         alchemy_connection)

        return(df_eval)

    else:

        print('pulling ids in range')

        pull_results_info = """
                select * from dssg_results.eval_meta
                where model_id >= {id_lower}
                and model_id <= {id_upper}
```

Ways we made more automatic

- Used config file that we drew upon and beginning of each model run (or "experiment") that drew parameters for that run

```yaml

## features
param_name_feature_lists: 'features_dictionary.yaml' # no need to change
param_features_to_pull: 'for_deep_dive' # choose sets of features to use

############ split dates to use
param_split_start_date: '2016-07-01' # pick first split date
param_split_end_date: '2017-12-01' # NOTE THIS IS A DUMMY FOR CONFIG DICTIONARY IN THIS RUN pick end date for te
param_split_increment: '1' # number of months to increment by

############# data to load
param_which_timeunit: 'month' # model isn't set up to run weekly, but we could make the split function dynamic (
param_label_type: 'binary' # choose whether to use binary, continuous, or ratio. Ratio means the building is in
param_primary_label: 'internal_cases_opened_any_next_month' # choose primary label to subset on for missingness
param_label_quantile_threshold: 0.9 # if primary label is a ratio, quantile threshold over which ratio is coded
param_only_observed_labels_train: True # choose whether to include obs with missing labels
param_test_targetzip: True # choose whether test data should include only addresses from TSU target zips

############ storing config file
param_update_config: True # whether to update master config file with parameters; set to false for test runs; Tr
param_return_all_config: False # whether to return the master config file; set to true if want to view for some

############# imputation methods
param_binary_features_imputation_methods: 'impute_median' # method to use to impute binary features: can be mean
param_continuous_features_imputation_methods: 'impute_mean' # method to use to impute continuous features: can b
param_label_imputation_method: 'None'

############# categorical encoding
param_threshold_for_dummy: 10 # how many distinct addresses a level of a categorical var needs to have in order

############# model params
param_unit_id: 'address_id'
param_time_id: 'month_start'
param_model_comment_toadd: 'None'
param_fileid_table_comment_toadd: 'None'
param_borough_fit_list: ['Bronx', 'Queens', 'Staten Island', 'Brooklyn', 'Manhattan'] # can be all 5 or subsets
param_borough_predict_list: ['Bronx', 'Queens', 'Staten Island', 'Brooklyn', 'Manhattan']
param_model_list: 'models_800ish'
```

Ways we made more automatic

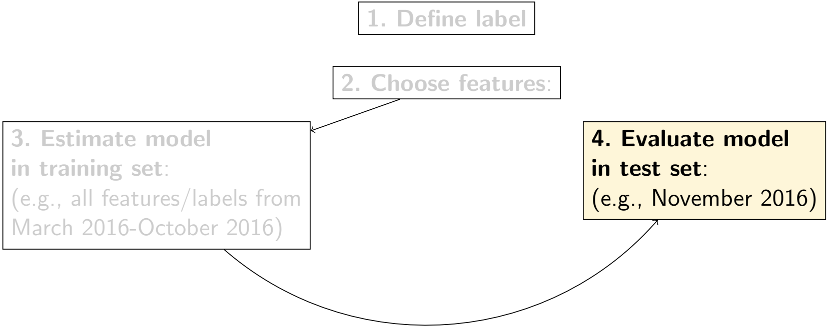
```
random.seed(20190307)
with open('/home/yet/nyc_peu_inspections/pipeline/models/experiments/parameters_0307.yaml','r') as stream:
        parameters = yaml.load(stream)

locals().update(parameters)
parameter_names = [key[0] for key in parameters.items()]
update_master_config_new(creds = creds,
                     parameter_names = parameter_names,
                     parameters = parameters,
                     update_config = param_update_config,
                     return_all_config = param_return_all_config,
                    simpler_loading = True)


log.info('updated master config')


models_dictionary = download_backups_s3('models_dict.yaml', creds,
                                  filetype_string = 'yaml')
model_list = models_dictionary[param_model_list]
## initiate cursor and alchemy connection
```

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

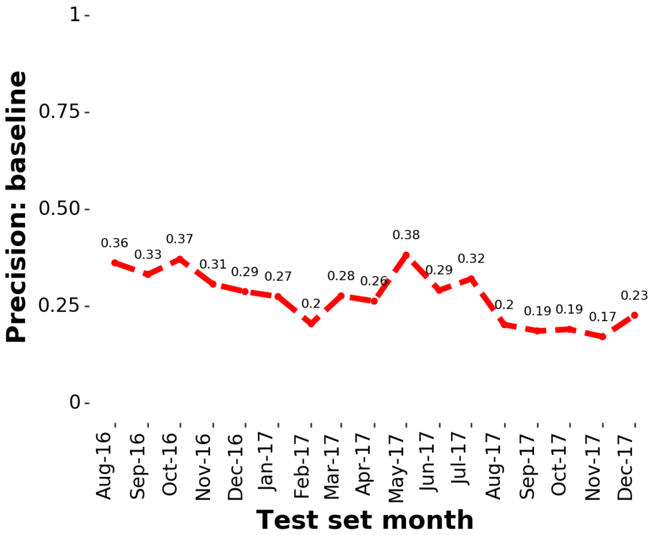


Steps in ML-guided prioritization: (1) define label; (2) choose features, (3) split data temporally and estimate model in training set, (4) evaluate performance in test set

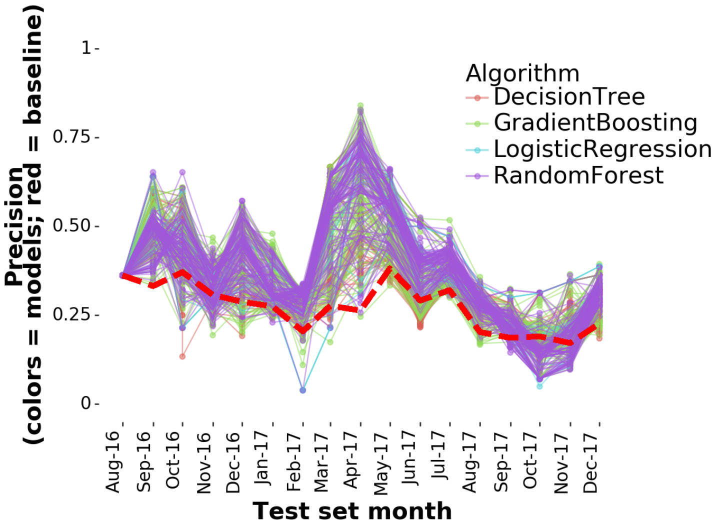
ID	Y **True label**	Score	$\hat{Y}$ **Pred. label**	# of units	# of cases
a5	1	0.8	**1**	153	34
a7	NA	0.79	**1**	23	NA
a8	0	0.65	**1**	77	0
Total units				*253*	
a4	NA	0.46	**0**	100	NA
a1	0	0.45	**0**	10	0

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

What we want to outperform: TSU's existing prioritization

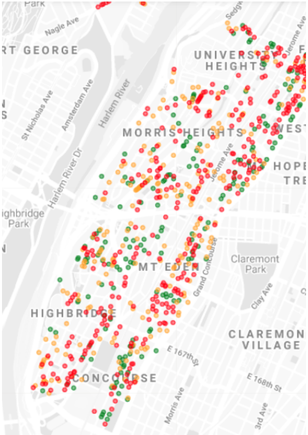


Nearly all models outperform that existing prioritization



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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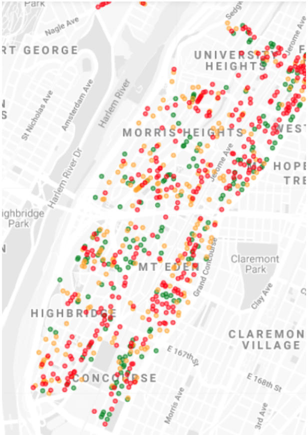

Staying at their same capacity to visit ∼ 60,000 residential units each year, 40-80% increase in performance:

- *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

- Mayor De Blasio: "We have teams knocking on doors in fast-changing neighborhoods"

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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))

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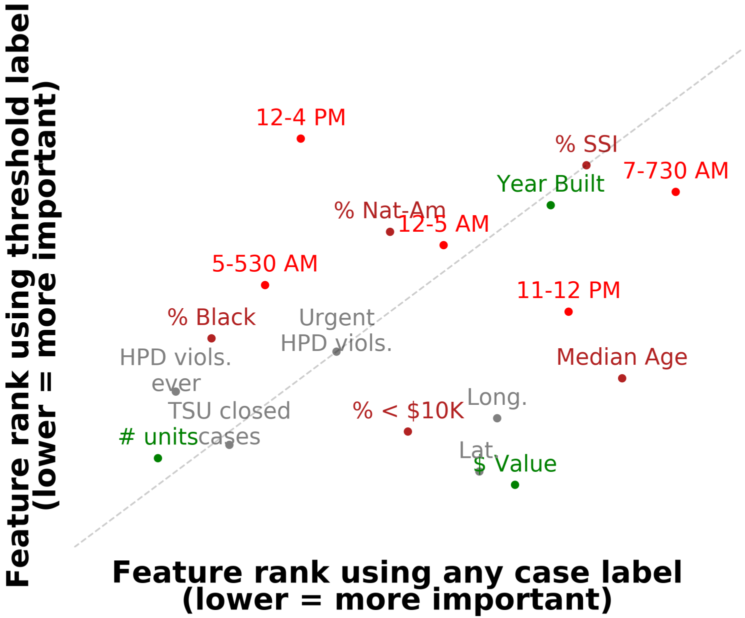
Type of neighborhood: "persistent poverty" (poverty + little increase in median income (2000-2010)

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
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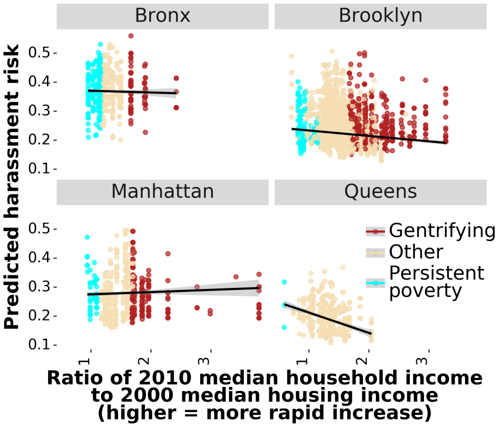
High predicted harassment risk in both gentrifying and persistent poverty neighborhoods



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!

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raj2@princeton.edu

Appendix

Background: policy levers to increase housing affordability

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

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

Target universe: buildings in
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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

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

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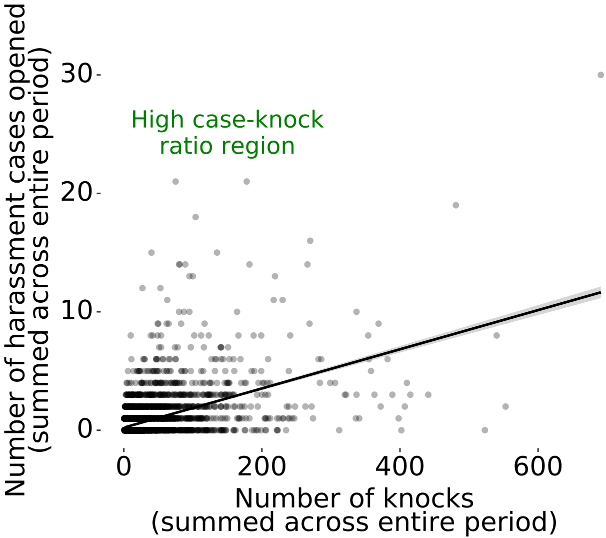

Features: details

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	

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⋮					
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

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Address ID	Score	# of Units	Pred. Label	True Label	# of Cases
a5	0.81	153	1	1	34
a7	0.68	23	1		
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Total units				*253*	
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4. Repeat for model $j+1$

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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)

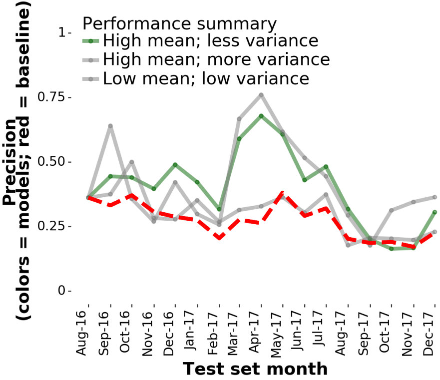
```
large_grid = {
    'RF':{'n_estimators': [1,10,100,1000,10000], 'max_depth': [1,5,10,20,50,100],
    'max_features': ['sqrt','log2'],'min_samples_split': [2,5,10], 'n_jobs': [-1]},

    '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

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

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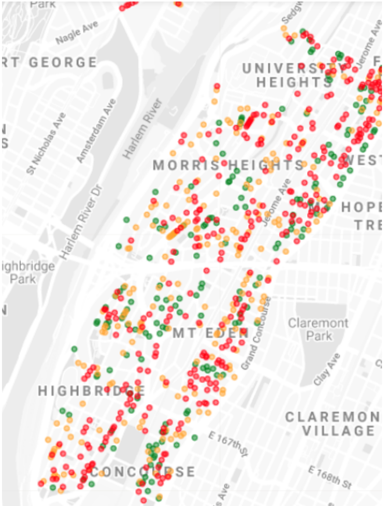
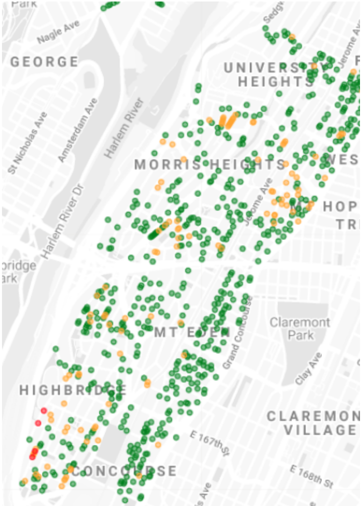
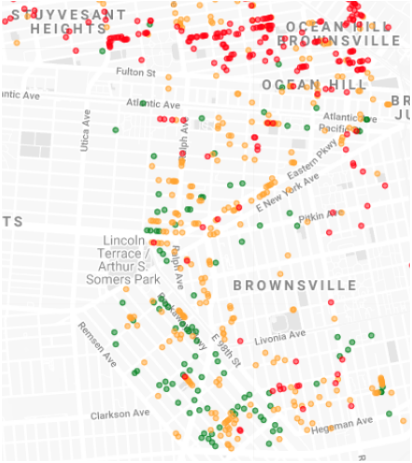


Case per units > threshold:

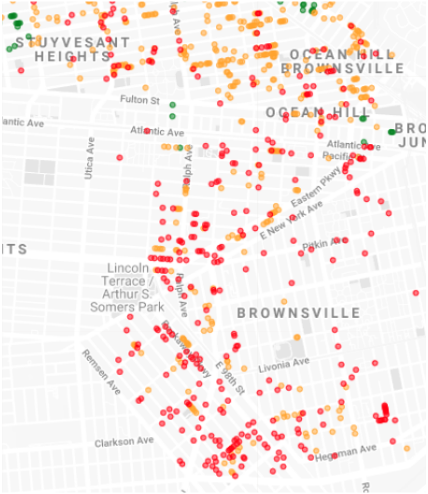


Risk tertile: area of Brooklyn under each label

Any case:



Case per unit $>$ threshold:



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  - Variation in that proportion is relevant

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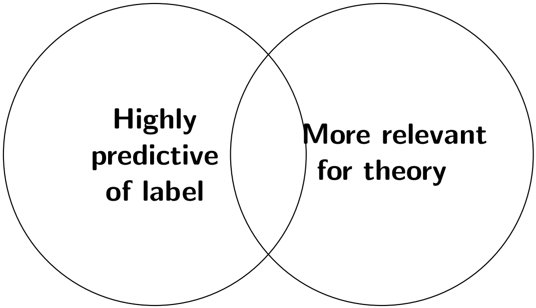
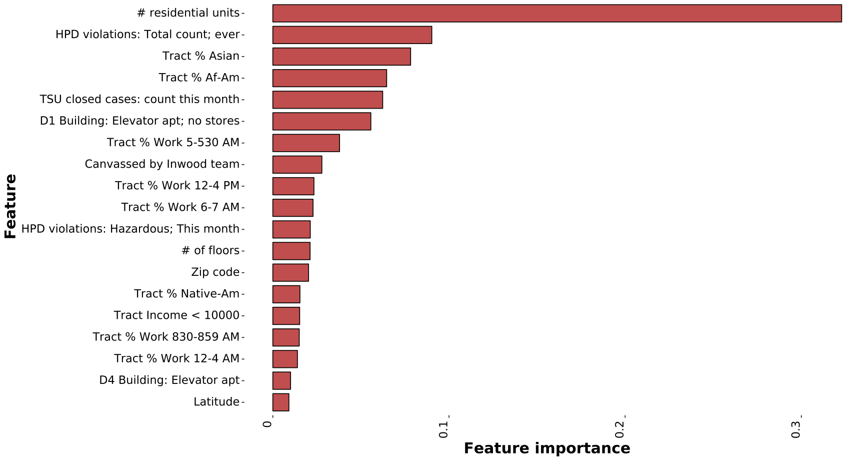
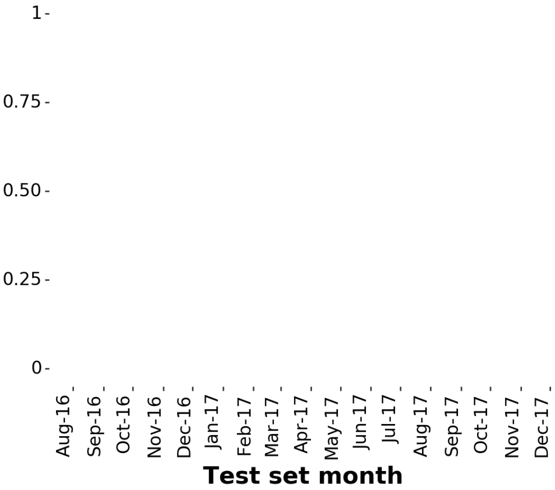
1. **Predictions**: fairness and variation in predicted risk under different label definitions
2. **Feature interpretation:** Goldilocks region:



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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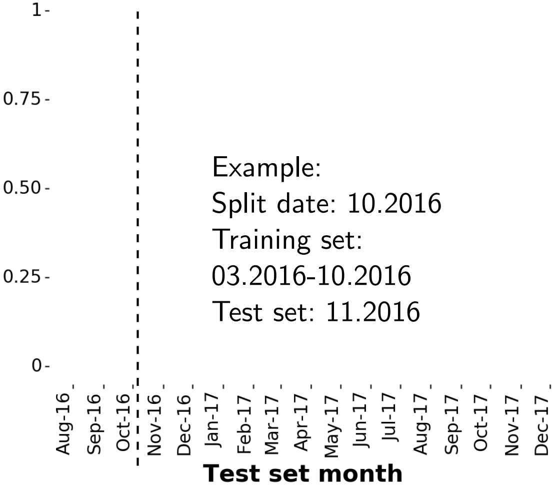

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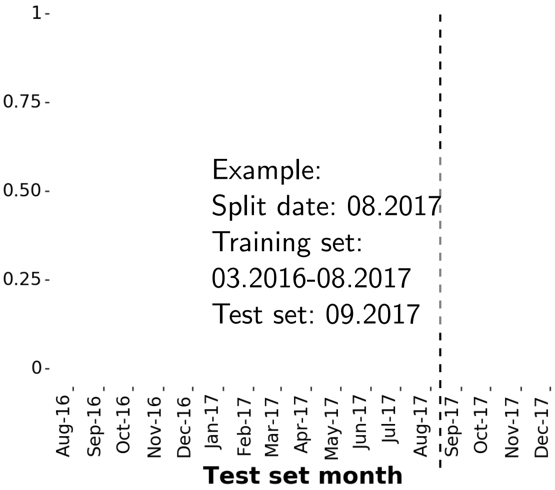
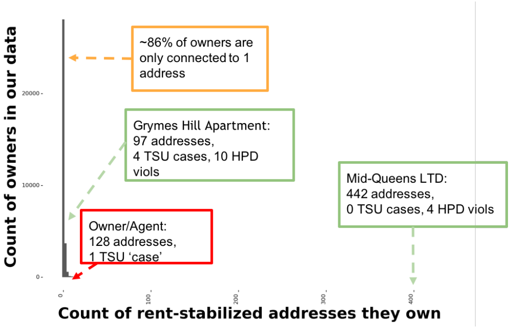


Features: relevant for theory but not highly predictive of label



Despite fuzzy string matching to map multiple spellings to same owner, e.g.:
BAINBRIDGE CLASTER AS
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- In turn, we might see same outcome–landlord harassment–in the two types of neighborhoods but for different reasons:
  - "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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