Understanding Blight Ticket Compliance in Detroit

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ABSTRACT

Property blight affects more than 20% of properties in Detroit. The City of Detroit issues tickets to owners of these blighted parcels, which incentivize residents to maintain their properties. However, the compliance rate for these tickets is under 10%, which leaves tens of millions of dollars in unpaid fines. In this paper, we seek to understand why compliance is so low and how violations could be better enforced to effectively address the city's blight epidemic. To this end, we build a predictive model that forecasts ticket compliance, perform in-depth analysis on the groups of residents who own blight-ticketed properties, and investigate how compliance varies between these very different groups.

1. INTRODUCTION

Properties not being properly maintained, cumulatively referred to as blight, are a widespread and costly problem in Detroit. The City of Detroit began issuing blight violation notices in 2005[1], commonly referred to as blight tickets, to encourage homeowners to keep their homes in good condition or else help finance the city's renewal efforts. The tickets range in value from \$20, for offenses including leaving out a trash bin too far before its collection date, to \$10,000, for offenses including dumping more than 5 cubic feet of waste[2]. When issued a ticket, a homeowner can either claim responsibility and pay the fine or attend the hearing to contest the fine; if someone fixes the violation before the hearing, that person would be deemed not responsible for the ticket [1]. However, the compliance rate for these tickets is abysmal: less than 10% of tickets where the homeowner is deemed responsible actually get paid, leaving some \$70,000,000 in unpaid blight tickets over the past 12 years.

Thriving with the growth of the auto industry, Detroit was once the fourth most populous city in the United States. However, loss of jobs in the auto industry and the suburbanization of the metro area contributed to Detroit's decline, which began in the mid 1960s. The following decades continued this slump; Detroit filed for bankruptcy in 2013, and the city's population has decreased from a peak of 1,800,000 in 1950 by over 60% to around 700,000 residents in 2017. The shrinking population has been accompanied in parallel magnitudes by the abandonment of buildings and vacation of lots [10]. Additionally, in 2005, sub-prime lending accounted for 68% of all mortgages in Detroit, 2.5 times the state sub-prime lending rate of 27%. These loans are designed for buyers with low credit and have high interest rates; they are over 4 times more likely to be defaulted on than non-sub-prime loans. In turn, Detroit has endured 65,000 mortgage foreclosures since 2005, totaling over 1/6 of the total number of parcels in the city. After foreclosure, 56% of those properties are now blighted or abandoned[12].

Figure 1: A blighted property in Detroit. This parcel has two unpaid blight tickets totaling \$500[2]. [Source: Motor City Mapping [5]]

In September 2013, the Obama Administration appointed the Detroit Blight Removal Task Force to address the city's problem with homes that are abandoned or in poor condition

[1]http://www.detroitmi.gov/How-Do-I/Pay/Blight-Ticket-FAQ

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by making a plan to remove all heavily-blighted structures and lots. From December 2013 through January 2014, all 380,000 real estate parcels within city limits were surveyed, and 84,461 of those were deemed to be blighted: 73,035 were residential, 6,135 were vacant lots, and 5,471 were non-residential properties[6]. While the task force determined that it is possible to remove all blight in the next 5 years, the price tag on this mission is not small: it is expected to approach $2,000,000,000.

The Michigan Data Science Team is a student organization at the University of Michigan that brings together students with an interest in data science to promote data science knowledge, organize and compete in competitions, and collaborate with external organizations to work on projects. Officials from the City of Detroit who work with blight tickets and the Michigan Data Science Team initially came together this past February to sponsor a competition exploring what makes a citizen comply with a blight ticket.

To provide a more actionable analysis for the City of Detroit, we aimed to understand what sorts of people receive blight tickets, how we can use this knowledge to better grasp why blight tickets have not been effective, and to provide insights for policy makers accordingly. To accomplish this, we aggregated many open datasets regarding various aspects of Detroit and its properties, built a model to predict whether a ticket would get paid, and analyzed the top violators as well as live-in homeowners and renters within residential properties.

2. BLIGHT DATA

In order to get an accurate picture of blight compliance in Detroit, we aggregated information from multiple datasets. All of this data is or has been publicly available, and most was retrieved from the Detroit Open Data Portal (Figure 2).

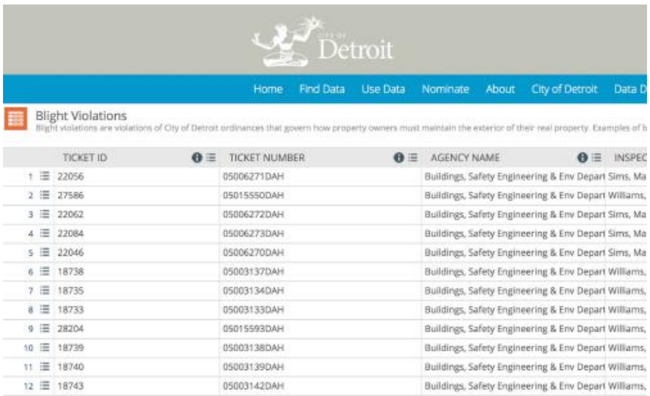


Figure 2: A screenshot of the blight violation data from the Detroit Open Data portal. Much of the data for this paper comes from this source.

2.1 Blight Ticket Data

Records for issued blight tickets are publicly available on the open data portal [2]. Records include the location of the blighted property, the address of the owner of the property, and a violation code indicating what kind of blight is present and a description of that violation.

One challenge presented by this data is that the addresses of the violations are filled in manually by the ticket issuer, leading to inconsistencies in recorded addresses. We used the Google Maps API to consolidate similar addresses.

2.2 Parcel Data

Parcel data [8] includes information such as the age, location, zoning information, and estimated value of a property. In order to merge this data with our blight ticket data, we needed consistent addresses across both sets. As with the blight ticket data, we queried the recorded parcel addresses the Google Maps API and retrieved the first result. By using this search technique, we were able to merge parcel data into 93% of the blight ticket data. Merging without cleaning the addresses with the Google Maps API yielded very poor results.

2.3 Crime Data

All recorded crimes from 2009 to May 2017 were also publicly available online (the dataset has since been archived). There are more than 3 million records in this data set. Records include where and what kind of crimes are reported, divided into 28 categories. To merge these records with the parcel data we drew a 0.25 kilometer bounding circle around the recorded latitude/longitude coordinates of each parcel and counted the number of each type of crime that occurred therein. The choice of 0.25 kilometers was chosen heuristically to improve our predictions (see Section 3).

2.4 Demolition Data

Detroit has many abandoned properties due to its shrinking population [10]. The city is working to demolish many of the structures on these properties and has made data available [4] [3] about which properties have already been demolished and which are scheduled to be demolished in the future. Similar to the crime data set, we incorporated this into the parcel data by drawing bounding circles around each property and counting the number of past and scheduled demolition within its boundary.

2.5 Improve Detroit

Detroit crowd-sources neighborhood issues through a mobile application and web platform called Improve Detroit [2]. Citizens are encouraged to report potholes, fallen trees, and instances of blight. These reported issues are categorized and made publicly available [7]. We connected reported issues to parcels using the same bounding circle technique and counting the number of issues in each category.

3. PREDICTING BLIGHT TICKET COMPLIANCE

In this section we present the data challenge that began our collaboration with the City of Detroit, the predictive models we then made for blight compliance, and an investigation of

[2] http://www.detroitmi.gov/How-Do-I/Mobile-Apps/ImproveDetroit

important features. This helps us understand which data correlate strongly with blight compliance prediction, which in turn can help understand how compliance is shaped by policy.

3.1 Data Challenge

The Michigan Data Science Team partnered with the Michigan Statistical Symposium for Interdisciplinary Statistical Sciences to co-host a Data Challenge, a competition that sought to analyze why blight ticket compliance is so low. The challenge was sponsored by the Department of Innovation and Technology from the City of Detroit and the Department of Administrative Hearings from the City of Detroit. The data challenge had two components: (1) A visualization challenge, where participants prepared data visualizations that provided insights about blight ticket compliance; and (2) a prediction challenge, where participants predicted whether or not a ticket would get paid given information in the blight ticket dataset. While all entrants were encouraged to use data from the Detroit Open Data Portal, contestants were only provided a cleaned version of the dataset containing blight ticket information[2]; the datasets mentioned earlier were aggregated , Allie Cell and Jared Webb, as well as the first two prediction challenge competition's winners, Jared Webb and Xinyu Tan, have all continued working on this problem and are authors on this paper.

The visualization competition's entries included a variety of graphs comparing factors both within the blight ticket dataset and factors selected from other datasets hosted by the Detroit Open Data Portal and an interactive data map.

The prediction challenge was hosted on Kaggle inClass, and attracted 39 undergraduate, graduate, and post doctoral participants from the University of Michigan. The blight ticket data was split into a training set, made up of the tickets collected before 2012, and a validation set, comprised of the tickets issued during and after 2012. The target variable was whether or not a blight ticket would be fully paid within 1 month after the hearing data.


Completed • Knowledge • 24 teams
Detroit Blight Ticket Compliance
Mon 13 Feb 2017 – Wed 15 Mar 2017 (3 months ago)
Dashboard
Private Leaderboard - Detroit Blight Ticket Compliance
This competition has completed. This leaderboard reflects the final standings.

#	Δrank	Team Name	Score	Entries	Last Submission UTC
1	–	Jared Webb	0.83392	9	Wed, 15 Mar 2017 23:55:1
2	–	raskolnikov	0.82257	12	Wed, 15 Mar 2017 20:18:1
3	–	KS	0.82148	23	Tue, 14 Mar 2017 20:12:17
4	–	Arya	0.81529	5	Thu, 09 Mar 2017 22:38:07
5	–	mengbo	0.81102	27	Wed, 15 Mar 2017 23:29:5

Figure 3: The snapshot of top 10 teams on the leaderboard for the prediction challenge. The competition was facilitated by MDST.

3.2 Model Selection

There were 35 columns for each record in the blight data set; this number grew to over 800 after incorporating other datasets from the Detroit Open Data Portal and performing one-hot encoding on categorical data. All non-categorical data was left as it was, after preprocessing extracted raw numbers from monetary data.

It has been observed [13, p.552] that tree methods are easily interpretable and perform well for mixed data. We considered `scikit-learn` [14] Random Forests and the `xgboost` [9] Gradient Boosted Trees (`XGBoostClassifier`). To choose the best model we generated learning curves with 5-fold cross validation for each classifier. It should be noted that the folds were calculated across the entire training set, leading the classifier to predict compliance for tickets from all years before 2012. This is different from the validation set, which consists of tickets that were issued strictly after the training data.

While both models had similar cross-validation scores, the learning curve for the Random Forest classifier showed a consistent gap between training scores and test scores, indicating over-fitting. As shown in Figure 4, the `XGBoostClassifier` yielded no such gap and so was chosen as the better classifier.

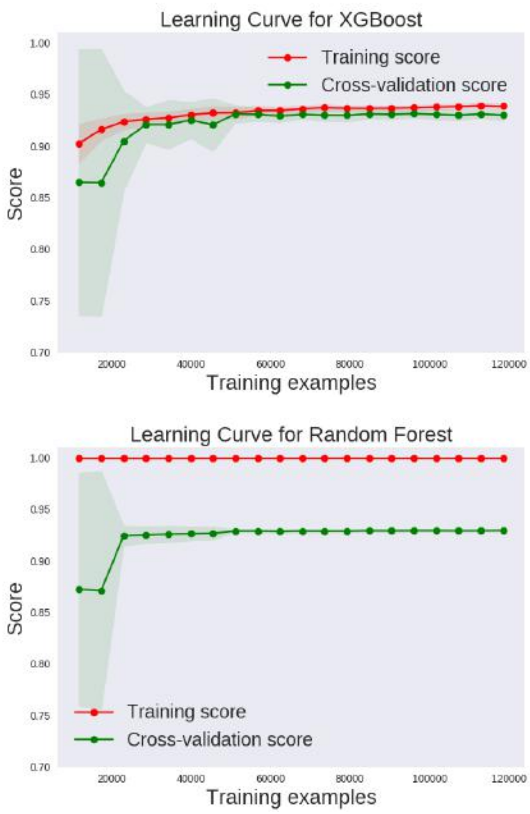


Figure 4: Learning curves for `XGBoostClassifier` and `RandomForestClassifer`. Note the gap between the training and crosss-validation scores for the Random Forest Classifier. A persistent gap combined with a perfect or near-perfect learning score is an indicator of overfitting.

To choose parameters for the `XGBoostClassifier` we performed a grid search on three model parameters with 3-fold cross validation. The parameters that yielded the best results were: 512 estimators, 0.1 learning rate and maximum depth of 7. These were then used to train a classifier on the training data.

4. PREDICTION RESULTS

The trained `XGBoostClassifier` model had a Area Under ROC score of 0.75, as can be seen in Figure 5. This is a discrepancy from our cross-validation scores, perhaps due to the the difference between the cross-validation folds and the validation set mentioned in Section 3. Table 1 gives the confusion matrix of the predicted labels. The classifier was able to predict accurately most of the true positives in the validation set, but at the cost of many false positives.

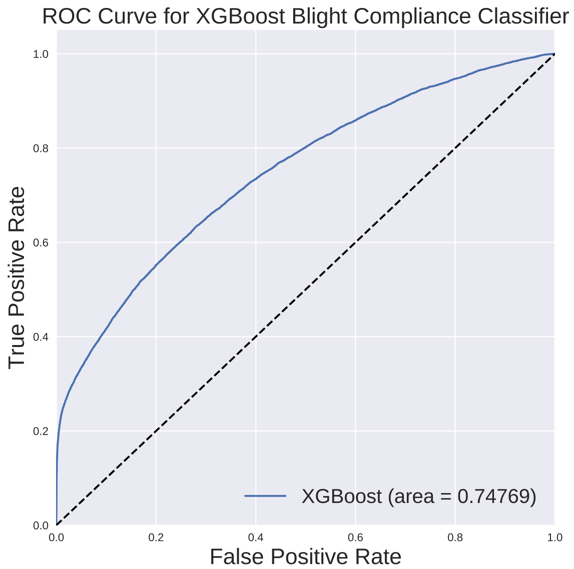


Figure 5: A ROC Curve for predictions from the `XGBoostClassifier`. The steep increase in the bottom left corner indicates that blight tickets with a high predicted probability of compliance were accurately labeled.

	Predicted Positive	Predicted Negative
Actual Positive	45086	481
Actual Negative	8295	3883

Table 1: Confusion matrix for predicted compliance from `XGBoostClassifier`. Note that the number of false positives is large, but the number of false negatives is relatively small.

To further interpret the results of the classifier we analyzed feature importances. Feature importance with tree ensemble methods can be determined by the number of times the individual trees in the forest split on each feature. The most predictive features for the `XGBoostClassifier` fall into several categories.

Physical Property Attributes. Unsurprisingly, the physical attributes of the building that receive a blight ticket are among the most important for predicting whether or not the property owner will comply with a Blight Violation Notice. Of these, the most important were the total building footprint, when the home was built, and the size of the parcel.

Economic Data. Economic data was also determined to be important according to our classifier. Factors in this subset include the property's state-assessed value and the most recent sale price of a parcel. It is also noteworthy that previous tax delinquency is one of the top 10 most predictive factors.

Human Data. Several features correspond to when a blight ticket is issued and when the hearing dates are scheduled. This was puzzling at first but discussions with the City revealed that the day of the week a ticket is issued corresponds to specific groups of officers that issue tickets. These groups are also assigned specific dates for their hearings. We do not know if different officers take different approaches to enforcement and ticket writing, but this result suggests that some officers are much more successful than others at writing tickets that will be complied with.

Demolition Data. Finally, the number of local demolitions and scheduled demolitions were determined important. This correlation is expected since Detroit is undergoing efforts to demolish its most blighted properties.

5. ANALYSIS OF TICKETED PROPERTY OWNERS

In order to provide more interpretable insights to policymakers in the City of Detroit, we sought to find out more about the people who receive blight tickets. Our analysis focused on the different relationships property owners have to their ticketed parcels, ranging from major offenders who have collected thousands of tickets on hundreds of different properties to owners who live in their ticketed residential house.

5.1 Major Offenders

We initially suspected that blight ticket compliance is so low because of the concept of issuing reasonably expensive tickets to people living in homes in poor condition. Once we discovered that many of the ticketed parcels are unoccupied, and some violators own multiple properties, the lack of compliance became a more complex issue. We verified the reported [15] existence of several "Blight Kings" in Detroit that own a significant amount of ticketed properties (blue bars in Figure 6). Finding that these top 20 offenders owns about 6.67% of the total fines, we further explored the importance of "the vital few" [3]. Out of a total \$ 73,718,641.0 in outstanding fines, 20% of the violators account more than 70% of the balance (Figure 7).

This led us to investigate how many bight tickets these major offenders have paid. Though these are typically large, well-funded organizations, their compliance was no better than

[3] https://en.wikipedia.org/wiki/Pareto_principle

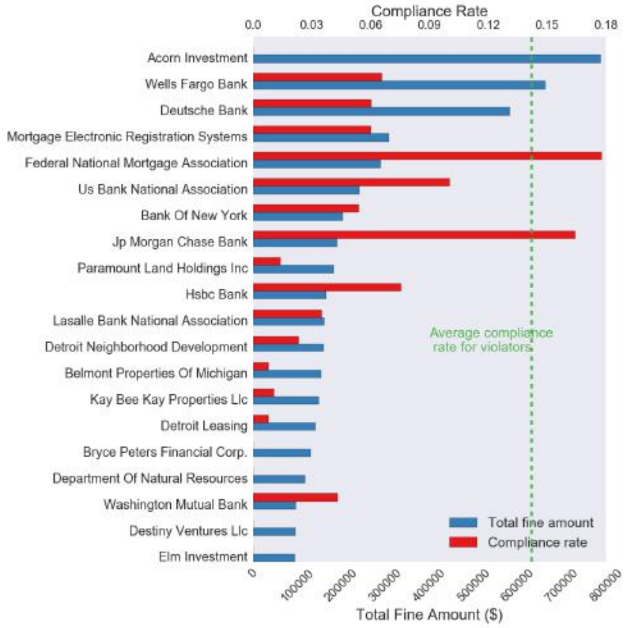


Figure 6: Total fine amounts owed and compliance rates for the top 20 "Blight Kings". Many of them have a below-average compliance rate.

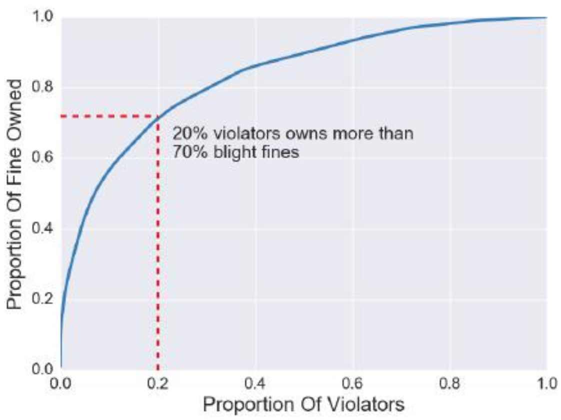


Figure 7: Illustration of the importance of "the vital few".

the rest of the city (red bars in Figure 6). We also observed that some of the top offenders have not paid any issued fines. What could affect these organizations' decision in paying or not paying? The same news report pointed out that some of the major offenders purchased cheap blight properties and profited from renting and selling them later [15]. The top 20 offenders owned an average of over 260 blight properties each. We were interested in seeing whether major offenders didn't pay blight tickets on properties that they deemed not worth it, but if they were more responsive to tickets issued to properties in better condition. If so, we were interested in what factors indicative of a parcel in good condition would matter. To dive into this inquiry, we looked into four aspects of the properties: sales price, usage, occupancy, and condition.

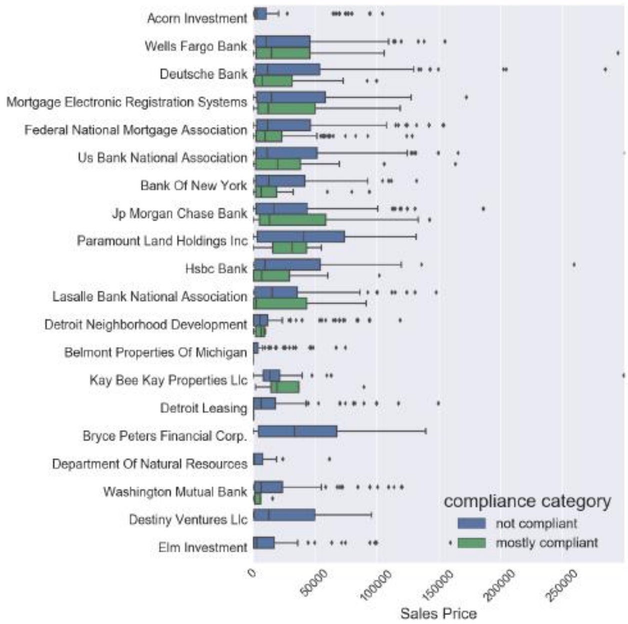


Figure 8: Sales price for blight properties owned by top 20 blight violators. Note that properties owned by Acorn Investment, Belmont Properties of Michigan, Department of Natural Resources, Elm Investment, and Washington Mutual Bank were purchased at particularly low prices.

We first wanted to see whether there is a difference in the sale price of properties whose tickets were paid by major offenders as opposed to properties whose tickets were not paid. We observed that many parcels have more than one ticket, but some could belong to different violators who purchased the parcels at different prices. To take this into account, we first grouped the tickets by violator, and then for each violator we calculated the average compliance rate for the parcel; we set a parcel "not compliant" if its ticket compliance rate is less than 0.3 and "mostly compliant" otherwise. For example, if a parcel received three tickets and paid one of those tickets off on time, we would deem it "mostly compliant". For each major offender, we plotted the box plot for the sales prices for "mostly compliant" and "not compliant" properties respectively (Figure 8). Though there is no clear trend that non-compliant properties were definitively sold at lower prices than compliant properties, we observe really low median sales price for some of the "Blight Kings". Notably, for 1021 properties that Acorn Investment owned, the median sales price was only \$3029.0, compared to \$7200.0 for all the ticketed properties.

In Figure 9, we provide further analysis of the usage, condition, and occupancy of these organization-owned blight properties. Similar to sales price, though we cannot draw a clear line between "not compliant" and "mostly compliant"

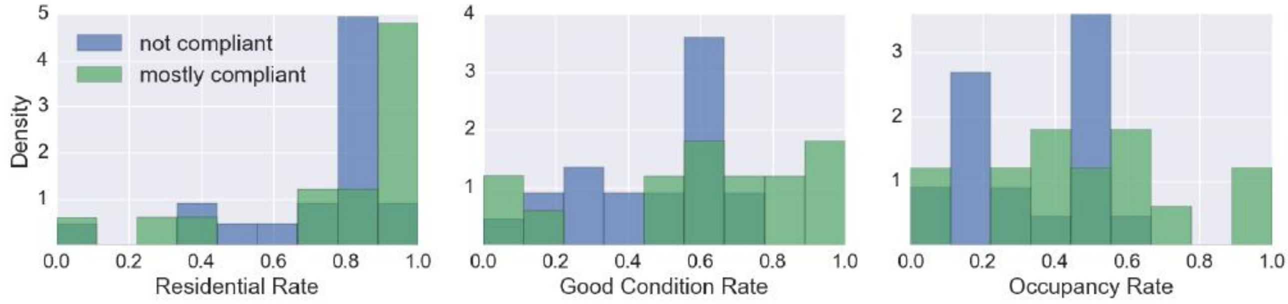


Figure 9: Top-20-offender-owned blight properties: Residential rate, good condition rate, and occupancy rate differ among "not compliant" and "mostly compliant" tickets.

properties, we observe that:

1. Except for the ones owned by Department of Natural Resources, the rest of top offenders owned an average of 75.0% residential properties. The "mostly compliant" group only averaged a 5% higher residential proportion.
2. On average, 58.6% of properties in "mostly compliant" group are in good condition, compared to 46.04% in "not compliant" group.
3. "Mostly compliant" properties are 16% more likely to be occupied.

Though there is no one clear cut to make between "mostly compliant" and "not compliant" properties, as we learned from the prediction challenge, by examining each group, we were able to gain partial insights into the properties, which will hopefully help guide policy decisions targeted at different groups. As our analysis revealed that residential properties make up most of the properties owned by top violators, we next seek to understand the situations of ticketed residential properties.

5.2 Residential Properties

Residential properties are of particular interest to our analysis for a number of reasons. From the perspective of blight enforcement and ticketing, working with a range of homeowners and renters is a very different task, compared to getting payment and cooperation from corporations and large companies. Additionally, residential properties made up 72% of all ticketed properties. Thus, out of all the various categories of properties (commercial, institutional, and residential), residential was the largest. Studying residential properties would also give us an opportunity to learn about the more overlooked communities in Detroit. This investigation has the potential to provide insight regarding the people who own these blighted properties, the conditions in which they live, and who bears the most suffering and responsibility in the situation. [4]

[4] A number of the properties that received tickets did not have any data for some of the attributes that were investigated. However, the percentages discussed are in relation to this full data set, which is why they do not total to 100%.

5.2.1 Grouping Properties

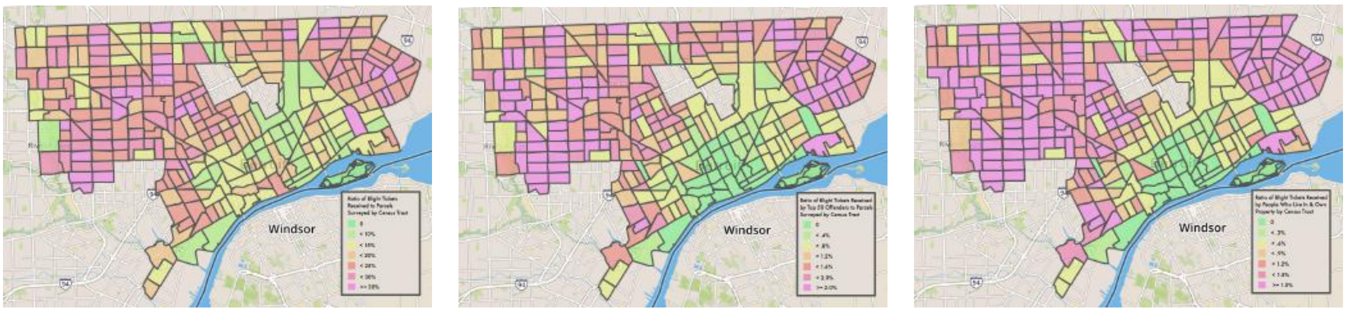
Within the realm of residential properties, a few natural groupings arose based on the available data and on our preceding analysis. We filtered out the properties belonging to the major offenders of unpaid blight tickets. This simply involved filtering out properties with violations issued to the top 50 names of offenders, as found in the preceding section.

From the remaining properties, two subgroups were created: homeowners and renters. More specifically, we wanted to discover what percentage of people who own a property actually live in this same property. To do this, we compared the addresses of the houses that received a blight ticket, and compared it to the mailing address to which the ticket was sent. Using this as the basis of whether or not the owner of the property does not reside at the home, we found that 28% of the violators lived in the properties in which they own, with the remaining being classified as "renters."

Interestingly, there were also indications within the data that a number of blighted properties were owned by city, state, or county governments. However, there were some problematic inconsistencies with the data in this regard. For example, the address of the supposed taxpayer of the property would indicate government ownership, but the violator names and mailing address would match up with those of one of the major blight offenders. There are a number of possible explanations for these inconsistencies in the data, including out of date government records, and the frequency with which these properties change owners. Ultimately, a more thorough investigation of this topic is out of scope. However, for consistency, we considered the mailing address of the ticket as the "living address" of the owner because this address was used at the time of the ticket's writing for the purpose of obtaining the fee. This makes it a logical choice to understand ownership and residency.

5.2.2 Ticket Values and Distribution

After constructing these groups, we first looked into the properties just owned by the top 50 major offenders of blight, as found in the last section. The average ticket value for these properties was about \$528, with a median value of \$250. Of the properties not owned by the major offenders, the median ticket value was \$250 and \$200 for renters and



(a) Density of all blight tickets

(b) Density of blight tickets amassed by the top 50 offenders

(c) Density of blight tickets by offenders determined to live in the property

Figure 10: Maps depicting the ratio of blight tickets received by groups to parcels surveyed by census tract.

owners, respectively. The average ticket fee for renters was \$317 and \$264 for owners. The major disparity between the average ticket fee for the major offenders and the other groups can be mostly explained by the much higher relative percentage of more expensive violations. In particular, the fees for having bulk solid waste on the premises usually exceeded \$2000, and these violations composed a higher percentage of the total violations incurred on this group, when compared to the others.

5.2.3 Repeat Offenders

There are a number of companies, organizations, and individuals that have collected many blight tickets. Extending this investigation further, we investigated this concept "repeat offenders" across the various groups. Of the violators who were classified as living on the property, 71% were first time offenders, and 18% were two time offenders. This supports the idea that those who live in these properties generally are not willfully and carelessly racking up violations. Renters have less control over the properties, and perhaps may also have less of an investment in maintaining the properties as well. The percentage of violators with more than 2 tickets almost doubled to 20%, with 59% first time offenders. Despite this, the large majority of violators are not chronic offenders, either. This stands in stark contrast to the "blight kings", who have all each accumulated many blight ticket violations. This strongly suggests that the major offenders are not likely to maintain, upkeep, or improve their properties in a responsible fashion, but still continue to purchase land parcels.

5.2.4 Occupancy Rates

Studying occupancy rates is helpful for learning more about the conditions and communities where people reside, but also has implications for enforcing blight tickets as well. Of the "major offender" owned properties, only 47% were actually occupied. In contrast, more than half of the 'rental properties' were occupied, at 57%. Most notably, properties that were considered to be resided in by the owner had an occupancy rate of 69%. This data backs the idea that the major offenders purchase and own many empty properties, and that people who own and live at a property are less likely to let the home become abandoned. This is a somewhat intuitive result: people do not want or lack the resources to move from the home they own. However, the low occupancy rate of the properties owned by the major offenders is troubling. It appears they purchase empty properties, and then fail to maintain them responsibly.

5.2.5 Property Conditions

Our data set also contained information about the conditions of these properties, as indicated by surveyors. Properties owned by the major blight offenders generally were in notably poorer condition when compared to the other groups. Only 63% of the properties were rated as being in "good" condition, while 24% and 8.8% were rated "fair" and "poor", respectively. Comparatively, 70% of the rental properties were in "good" condition with 20% and about 7.1% as "fair" and "poor" respectively. Of the properties lived in by our "homeowners" distinction, 76% were deemed "good" condition, 17% as "fair", and only 4.7% as "poor." It is difficult to draw exact conclusions from this data, but it continues to lend more validity to the idea that the major offenders do not maintain their properties. It also provides some backing to the intuition that someone who lives in the property takes the best care of the home and land, when compared to someone who owns a rental home or apartment.

5.2.6 Compliance

There were also some differences in ticket compliance between the various groups. We thought that it was important to account for tickets that were eventually fully paid, even if they were late. The compliance of major offenders is discussed at length in previous sections, but in the general context of residential properties, they were only 6.5% fully compliant, and paid another 19% of tickets late. Rented properties saw an improvement in this area, with 10% full compliance and another 12% late compliance. Properties lived in by the property owner were similar, at 11% and 13% full and late compliance, respectively. Overall, these numbers do show some trend in responsibility. The major blight offenders not only seem to do a worse job maintaining the properties, but also are less likely to pay a blight ticket on their properties as well.

5.2.7 Similarities

Because of how widely everything from cultures to renewal efforts vary by neighborhood in Detroit, we anticipated that the location of a parcel would be important in understanding compliance in blight tickets from the beginning of this project. As shown in Figure 10, we found a correlation between the density of blight tickets received by the top 50 offenders10b and the density of blight tickets received by owners determined to live in their property10c; the density of each demographic's tickets were lower than the overall density of blight tickets10a in the city's center, and higher in the Northeast and West sides of the city. While this could seem counterintuitive because major offenders have been made out to be the most harmful group and owners who live in their properties the least, in plainer terms this just indicates that areas of Detroit where people live in blighted properties also tend to be areas where major offenders own properties. Other similarities came from the parcel data. It is worth drawing particular attention to information about nearby demolitions. Across all groups, each ticketed parcel is within .25km of around 10 demolitions: 8.8 for live-in owners, 9.7 for renters, 10.3 for major offenders. While all of these numbers are similarly high, they don't necessarily indicate similar circumstances of the surrounding properties; demolitions are indicative of properties that used to be heavily blighted, but also that there is a focus on renewing that area. Additionally, on average, around 16-17% of these properties had some reported issues with illegal waste dumping on the premises.

6. CONCLUSION

Just as the widespread blight within Detroit is a result of many different factors over the last fifty years, there are a variety of different subsets of people receiving blight tickets. Our analysis demonstrates that a main factor in the ineffectiveness of blight tickets is issuing the same set of tickets without regard for who owns the property or under what circumstances that owner possesses the parcel. The City of Detroit has started taking action against these major blight offenders, including not being able to collect rent on blighted properties or being able to purchase any additional properties if they owe outstanding blight tickets. Based on our analysis, these measures would likely be more effective because they target people profiting off of their properties as opposed to those who live in their properties. We hope that similar adaptions to blight enforcement result from the collaboration and analysis detailed in this paper, and that data science will become more widely used to understand and improve policymaking.

Acknowledgments

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