A Machine Learning Approach on Providing Recommendations for the Vacant Lot Problem

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# Vacant Lots

What is a vacant lot?
An abandoned property
Caused by economic decline
Why are vacant lots a problem?
Criminal activities
Poorer standard of living
Depressed property value



# Reclaiming Vacant Lots

 Convert into community gardens
 Convert into urban farms
 Convert into Qualified Community Managed Open Spaces (QCMOS)



# **Current Approach**

Urban planners and community leaders select vacant lots for conversion
 Community programs provide support with data
 Decision is made by analyzing the data

Decision is made by analyzing the data and selecting a vacant lot



# **Problems with Current Approach**

 Decision is made by analyzing the data and selecting an optimal vacant lot

• Community leaders need to "reinvent the wheel" each time

### **Proposed Solution**

A system that would:
 Learn from previous vacant lot conversions and,
 Provide recommendations on which lots should be converted

# **Proposed Solution Benefits**

• Provide a decision support system for urban planners in tackling the vacant lot problem

Provide a recommendation tool for community members in a vacant lot

# **Research Objectives**

- Build a generalized vacant lot model that can be applied to any city
- Develop a machine learning model to predict vacant lot conversions

# The Vacant Lot Model

 We define a vacant lot as a dependency of its feature set F such that:

 $F = \{f1, f2, f3, f4, f5, f6\}$ 

f1 = Utility from public services and infrastructure f2 = Access to vacant lot f3 = neighborhood property value indicator f4 = vacant lot density

- f5 = crime density
- f6 = zoning policies

# Datasets

#### Baltimore

#### Philadelphia

O Size

• Vacant:

**O** 500

Converted class:
 COMMUNITY GARDENS - 601



### Vacant Lots in Philadelphia





# **Classification Models**

- Random Forest
- O Multilayer Perceptron
- O K-NN
- Naïve Bayes
- O SVM

# Methodology

 Build datasets in conformance with our vacant lot model
 Build classification models for each city • For each city

- Split dataset into training, testing and validation set
- Utilize random sample of 60% of the data for training and testing
- Utilize random sample of 40% of the data for validation

Classifier	ADOPTED			QCMOS			URBAN FARM			Overall (Mean)		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Random Forest	0.90	0.94	0.92	0.84	0.77	0.80	1.00	0.98	0.99	0.91	0.90	0.90
k-NN	0.91	0.94	0.92	0.85	0.79	0.82	1.00	1.00	1.00	0.92	0.91	0.91
Naive Bayes	0.79	0.98	0.88	0.91	0.44	0.59	1.00	0.98	0.99	0.90	0.80	0.82
MLP	0.81	0.92	0.86	0.75	0.54	0.63	0.98	0.98	0.98	0.85	0.81	0.82
SVM	0.85	0.90	0.88	0.78	0.65	0.71	0.95	1.00	0.97	0.86	0.85	0.85

### **Results for Baltimore**

Classifier	Adopt						
010001101	Precision	Recall	F1				
Random Forest	0.90	0.93	0.92				
k-NN	0.85	0.84	0.84				
SVM	0.67	0.72	0.69				
MLP	0.63	0.79	0.70				
Naive Bayes	0.76	0.72	0.74				

**Results for Philadelphia** 







### **Rochester Visual Predictions**



Integrated in a decision support system for city planning
 Integrated into vacant lot toolkit, recommending vacant lot selections for community members



Further research on the field can focus on:
 Applications on more cities
 Optimize with the use of geospatial attributes such as:
 OSatellite Imagery
 OGeographically weighted regression model etc.

# Conclusion

• The objectives of this research were:

- Design and development of a vacant lot model
- Building several prediction models for sample datasets
- Evaluating each prediction model and analyzing their results

#### • The findings were:

- Machine learning models are feasible for predicting vacant lots
- For our experiments, Random Forest classifier provided the best result
- Further validation with expert urban planners will provide a better evaluation