Project Proposal

INTRODUCTION

In any survey that requires physical mail materials, or campaigns of any sort that must be done in-person and door-to-door, the use of resources quickly can become an issue. For every house and business and person that you must reach, another physical object (e.g., a paper survey) must be produced and given to the person receiving the survey materials. A prudent campaign manager needs to make sure that they send their staff to the correct locations, with an accuracy as close as possible to 100%. Mistakes or incomplete information on the type of building and occupant can happen, which lowers the accuracy of the campaign and thus needlessly increases the budget and lengthens the survey campaign duration. In fact, in the CE Interview Survey from 1997-2000, 46% of the sampled cases were sourced from unqualified building units.[1] These errors could be due to many factors, but in this project, we focus on addressing accuracy issues related to construction, demolition, and non-residential structures. We propose a method to screen out locations which are ineligible for surveys and canvasses. This has the potential to dramatically lower costs for future survey campaigns, such as the 2030 decennial census.

PROPOSED METHOD

Our approach involves identifying areas of change in orthoimagery (i.e., "birds-eye" or top-down view) and then collecting facade-view imagery (e.g. Google Street View) of the areas that changed to classify structures based on their condition and type. It could also involve a tool where someone can input an address, a coordinate pair, or a list of either, and receive information on which buildings should be screened out of the survey. The condition and type classifications are currently the following (subject to change as the project develops):

- Residential
  - Blighted Residential
  - Demolished Residential
- Non-Residential
  - Blighted Commercial
  - Demolished Commercial

To do this, we will train a deep learning image model on facade-view imagery with those type labels. The change detection model has already been trained in our prior project (https://github.com/RevealGC/low-res-change-detection), which demonstrated how business owners can save money on expensive, high-resolution imagery by using low-resolution satellite imagery to detect change. This project could borrow a lot of the methods from the previous project too, like storing the data on an S3 bucket.

POTENTIAL DATA SOURCES

Labelled Data

In order to train the model, we will need to have a ground truth source; we will need to have labelled data to tell the model what kind of building it is and whether it is blighted or demolished.

We were able to find datasets for the following:

- Demolished buildings in Baltimore (source: https://data.baltimorecity.gov/datasets/baltimore::completed-city-demo-1/explore?showTable=true)
- Blight violations in Detroit (source: https://data.detroitmi.gov/datasets/f9e612a5a19b42e1a19524fd591acb7b_0/explore?location=42.319342,-83.094427,15.06&showTable=true)
- Residential demolitions in Detroit (https://data.detroitmi.gov/datasets/f8e2e053c73b4c98ada7fa32a19d6183_0/explore?location=42.350210,-83.094408,10.43)
- Commercial demolitions in Detroit (https://data.detroitmi.gov/maps/9c2f2bfa12404e6481e1624700e34cce/about)

Orthoimagery

Our previous efforts made exclusive and extensive use of Google Earth Engine's Python API to retrieve Sentinel-2 orthoimagery. We gathered these data into complex "datacubes" of repeat satellite images of the same area that the model used to learn how landscapes change over time. We can use the same approach for this project. It might be worth exploring other data sources of higher resolution, but that will come at a cost — Google Earth Engine's Sentinel-2 imagery is free.

Facade-View

There are a handful of providers of street view data, with some relying on first or second party sources and others taking an open-source approach. Google Street View is the most well-known provider of this data. Their API is robust and is well-documented when it comes to cost of use. There is a free tier but it is limited with a daily data request cap. Mappilary[2] is a service using an open-source approach. Their API is also well-documented and is completely free. (Meta bought Mapillary in 2020 and since then has an entirely free platform.[3])

Below is a table outlining the current pricing for Google Street View[4,5]:

Tier	Rate ($/1,000)
Free tier	0.00
10,001 – 100,000	7.00
100,001 – 500,000	5.60
500,001 – 1,000,000	4.20
1,000,001 – 5,000,000	2.10
5,000,001	0.53

There is a $300.00 credit given to new users. As of this writing, I have not used any.

To give a sense of what this project might require, let's use the Baltimore Demolitions dataset: There are 4,061 records total. Google started recording facade-view imagery for Baltimore in 2008.[6] To get a dataset of the buildings before and after demolition, if we assume 1) perfect coverage once a year, and 2) the demolition occurred sometime between 2008 and today, then we would have a maximum of:

$$18 \text{ images since } 2008 \times 4061 \text{ total records} = \mathbf{73,098} \text{ total images.}$$

As this number is less than 100,000, this would cost nothing.

However, looking at the Detroit blight dataset, with a maximum of around 800,000 viable records, the amount of street view imagery would be a maximum of:

$$18 \text{ images since } 2008 \times 800{,}000 \text{ records} = \mathbf{14,400,000} \text{ total images}$$

This would cost a lot of money:

Tier	Requests	Rate ($/1 000)	Cost ($)
Free tier	10,000	0.00	0
10,001 – 100,000	90,000	7.00	90 × 7.00 = 630
100,001 – 500,000	400,000	5.60	400 × 5.60 = 2,240
500,001 – 1,000,000	500,000	4.20	500 × 4.20 = 2,100
1,000,001 – 5,000,000	4,000,000	2.10	4,000 × 2.10 = 8,400
5,000,001	9,400,000	0.53	9,400 × 0.53 = 4,982
Total	14,400,000		**$18,352**

While Google Street View comes at a cost, you're getting high-quality images and metadata. Mapillary, on the other hand, is completely free, but the image quality, coverage, and image options (like heading, field of view, and pitch) are not as adjustable. As of right now, I am not satisfied with Mapillary's ability to give me an exact equivalent of Google Street View.

Clearly, we do not want to blindly go forward with Google Street View and spend tens of thousands of dollars on imagery. I think there is a way to retrieve targeted, high-quality training data while keeping the cost reasonable - perhaps up to hundreds of dollars, rather than tens of thousands of dollars. There's the added benefit of the free tier, where the 10,000 requests reset every month. We could build out a dataset over a few months to keep costs low, and supplement with Mapillary should I get a better handle on how to use their services.

We could also explore other sources of data, like parcel, zoning, POI datasets[7], and other information, that could supplement the satellite imagery. A lot of these sources of data are free.

CONCLUSION

Let's put aside the question of cost on the street view imagery, which is no small thing, I acknowledge. Instead of retrieving facade-level data for **all** of our Baltimore and Detroit datasets, to have one-to-one coverage, we could instead use a small, high-quality subset. With this subset, I believe that this project would be able to train a model that could predict with high accuracy whether a building is demolished, and whether it is commercial or residential.

[1] Lee, A., Ratcliffe, M., and Alter, S. (2025). Project Proposal Using Satellite Imagery for Pre-Screening Ineligible Housing Units.

[2] https://www.mapillary.com/

[3] https://help.mapillary.com/hc/en-us/articles/8348198426396-Mapillary-FAQ

[4] https://developers.google.com/maps/billing-and-pricing/pricing#map-loads-pricing

[5] https://developers.google.com/maps/billing-and-pricing/pricing#maps-2d-and-street-tiles-pricing

[6] https://maps.googleblog.com/2008/11/street-view-elects-dc-baltimore-and.html

[7] https://opensource.foursquare.com/os-places/