

# Beyond the Façade: Using Façade-View Imagery and Deep Learning to Predict Likelihood of Demolition

Samuel Alter

Senior Analyst, Data Science

Reveal Global Consulting | GWF: Amsterdam '26

# Agenda

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# Meet the Speaker

1

# Meet the Speaker



Samuel  
Alter

Senior Analyst, Data Science

# Meet the Speaker



Samuel  
Alter

Senior Analyst, Data Science

Geospatial data scientist and trained geologist

- Prior career in environmental consulting

Reveal Global Consulting is a data consultancy specializing in federal, state, and local government contracts

# Acknowledgements



Lei Peng  
Senior Data  
Engineer



Michael  
Ratcliffe  
Senior Advisor



Taylor J. Wilson  
VP, Applied Statistics  
and Data Science



Angi Lee  
Director, Reveal Labs



Hector  
Ferronato  
VP, Engineering

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# 2

## Context

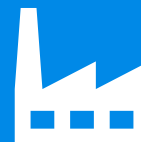
# Context

# Context

Building intelligence is relevant for surveys and tracking health of neighborhoods

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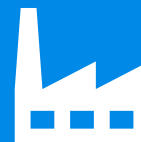
Building intelligence is relevant for surveys and tracking health of neighborhoods



# Context

Building intelligence is relevant for surveys and tracking health of neighborhoods

- Address sample selection for surveys must statistically robust and trustworthy

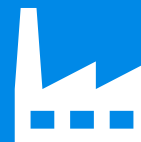


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Building intelligence is relevant for surveys and tracking health of neighborhoods

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For a residential survey, address must represent:



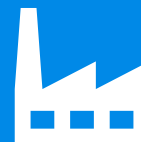
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Building intelligence is relevant for surveys and tracking health of neighborhoods

- Address sample selection for surveys must statistically robust and trustworthy

For a residential survey, address must represent:

- A residence
- Not demolished



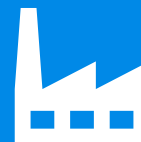
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- Address sample selection for surveys must statistically robust and trustworthy

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- Number of occupants must be accurate



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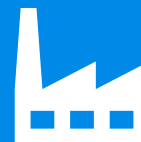
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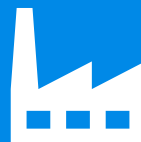
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- In-person observation and canvassing



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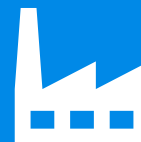
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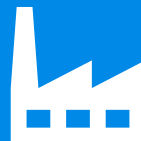
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- County-by-county data collection



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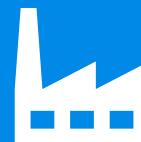
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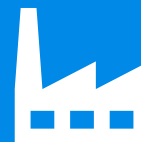
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- In-person observation and canvassing – *costly*
- County-by-county data collection – *time-consuming*
- Remote methods



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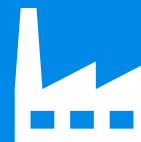
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- **Remote methods**



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# Goal

# 3

# Goal: Two-Stage Model

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Stage 1: Dereliction detection model

# Goal: Two-Stage Model

Stage 1: Dereliction detection model



*Is* this  
residence  
derelict or  
abandoned?"

# Goal: Two-Stage Model

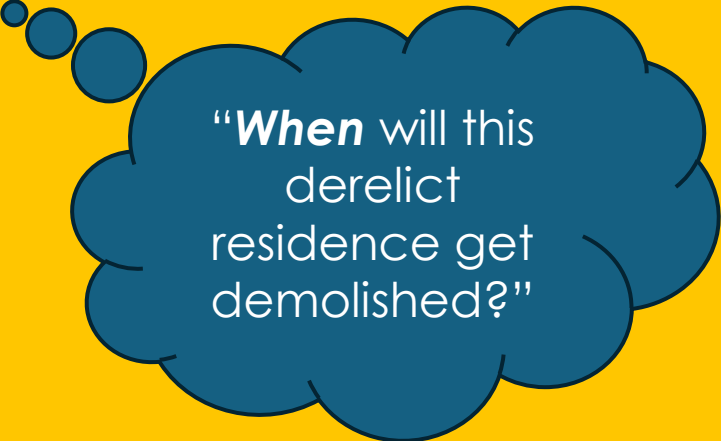
Stage 1: Dereliction detection model

Stage 2: Demolition prediction model

# Goal: Two-Stage Model

Stage 1: Dereliction detection model

Stage 2: Demolition prediction model

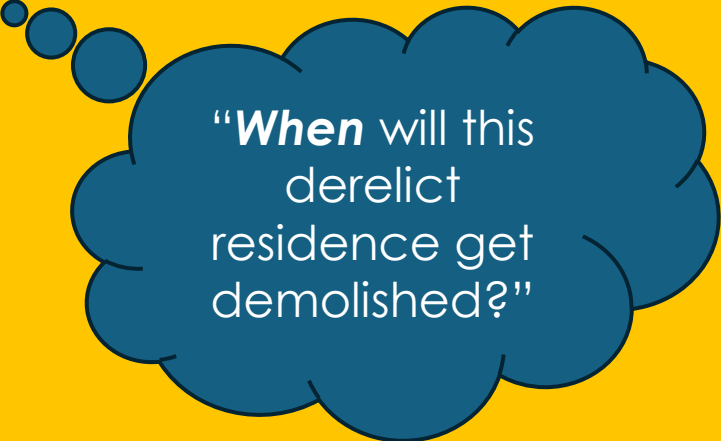


**“When** will this  
derelict  
residence get  
demolished?”

# Goal: Two-Stage Model

Stage 1: Dereliction detection model

**Stage 2: Demolition prediction model**



**“When** will this derelict residence get demolished?”

# Goal

Develop an approach that automates the pre-survey procedure, specifically whether a residence should be removed from an address list due to demolition within a time horizon

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Develop an approach that automates the pre-survey procedure, specifically whether a residence should be removed from an address list due to demolition within a time horizon

Be as frictionless as possible:

- Bulk or single address input
- Display retrieved façade imagery

# Goal

Develop an approach that automates the pre-survey procedure, specifically whether a residence should be removed from an address list due to demolition within a time horizon

Be as frictionless as possible:

- Bulk or single address input
- Display retrieved façade imagery
- Output demolition prediction

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# METHODOLOGY

# Methodology – Overview

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1. Acquire data of demolished homes

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2. Acquire façade imagery

# Methodology – Overview

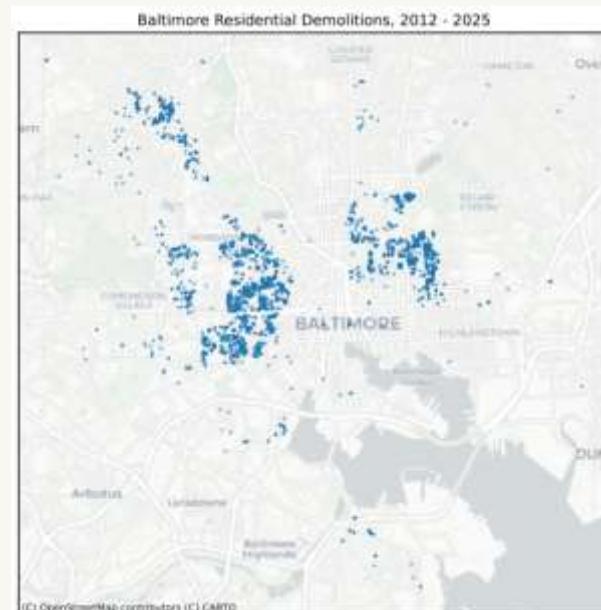
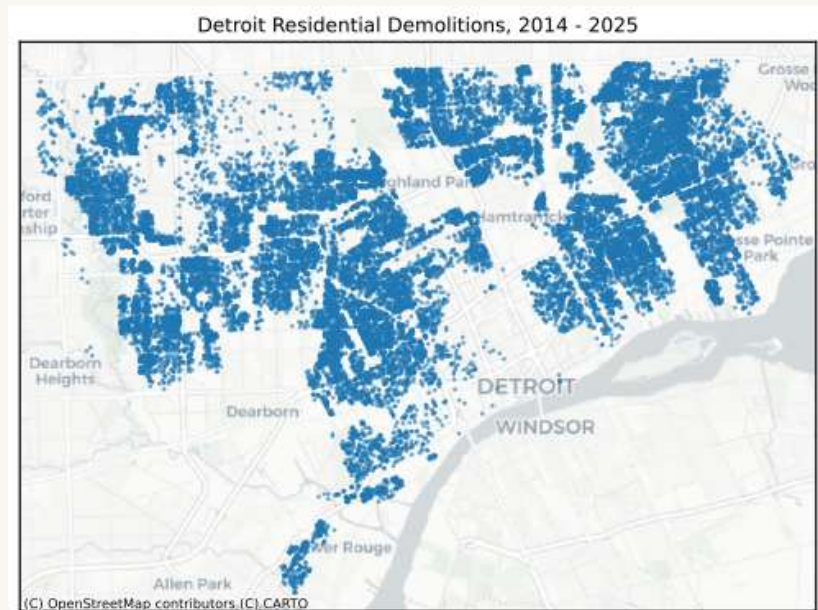
1. Acquire data of demolished homes
2. Acquire façade imagery
3. Train model to draw masks on façades in imagery

# Methodology – Overview

1. Acquire data of demolished homes
2. Acquire façade imagery
3. Train model to draw masks on façades in imagery
4. Train demolition model to predict likelihood of demolition within 48 months

# Methodology – 1. Demolition Data

# Methodology – 1. Demolition Data



# Methodology – 1. Demolition Data



Detroit



Baltimore

**Data for *residential homes* includes  
*location and demolition date***

# Methodology – 2. Façades

October 2007



Google

November 2020



Google

# Methodology – 2. Façades

Image retrieval pipeline

October 2007



November 2020



# Methodology – 2. Façades

Image retrieval pipeline

- Google Street View API

October 2007



November 2020



# Methodology – 2. Façades

Image retrieval pipeline

- Google Street View API
- OpenStreetMap

October 2007



November 2020



# Methodology – 2. Façades

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- Google Street View API
- OpenStreetMap
- Municipal parcel data

October 2007



November 2020



# Methodology – 2. Façades

Image retrieval pipeline

- Google Street View API
- OpenStreetMap
- Municipal parcel data

User Interface

October 2007



November 2020



# Methodology – 3. Masking

October 2007



Google

November 2020



Google

# Methodology – 3. Masking

Frozen SAM2 image encoder



October 2007



November 2020



# Methodology – 3. Masking

Frozen SAM2 image encoder

- Trained lightweight 3-class head on gold labeled masks



October 2007



November 2020



# Methodology – 3. Masking

Frozen SAM2 image encoder

- Trained lightweight 3-class head on gold labeled masks



October 2007



November 2020



# Methodology – 4. Model

October 2007



Google

November 2020



Google

# Methodology – 4. Model

Data exclusively of demolished homes

October 2007



Google

November 2020



Google

# Methodology – 4. Model

Data exclusively of demolished homes

Training data usage: **29,052** total images

- Train images: **24,289**
- Val images: **2,323**
- Test images: **2,440**

October 2007



November 2020



# Methodology – 4. Model

Data exclusively of demolished homes

Training data usage: **29,052** total images

- Train images: **24,289**
- Val images: **2,323**
- Test images: **2,440**

Base rate at  $\leq 48$  months: **28.7%**

October 2007



November 2020



# Methodology – 4. Model

Data exclusively of demolished homes

Training data usage: **29,052** total images

- Train images: **24,289**
- Val images: **2,323**
- Test images: **2,440**

Base rate at  $\leq 48$  months: **28.7%**

Trained on gold, silver, and bronze-tier masked façade imagery

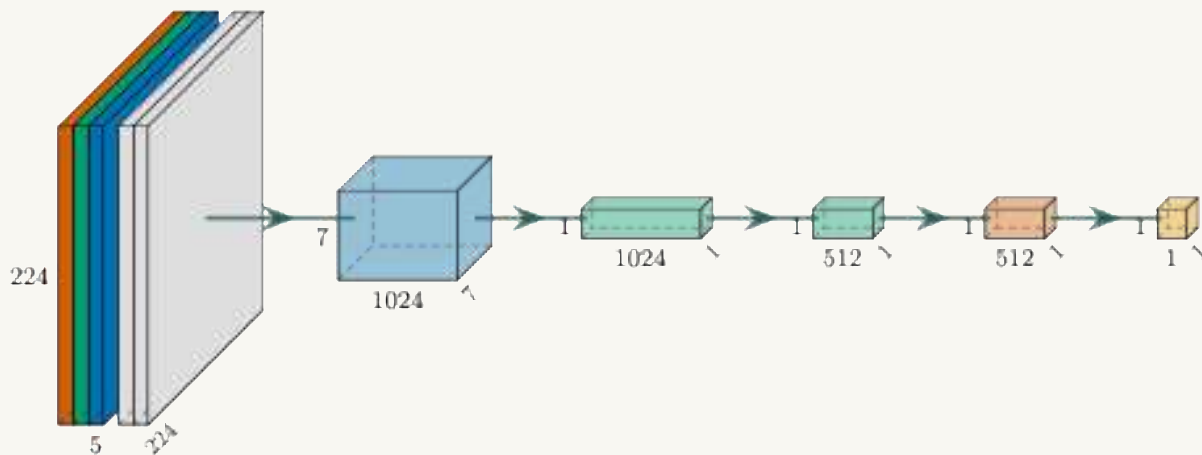
October 2007



November 2020



# Methodology – 4. ConvNeXt Model



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# Façade Model and User Interface

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# Façade Model



# Façade Model

Goal: Predict likelihood of demolition **within 48 months (1460 days)**



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Find a prediction threshold that maximizes recall with precision  $\geq 0.80$



# Façade Model

Goal: Predict likelihood of demolition **within 48 months (1460 days)**

Find a prediction threshold that maximizes recall with precision  $\geq 0.80$ : **0.7891**



# Façade Model – Confusion Matrix Examples

Goal: Predict likelihood of demolition **within 48 months (1460 days)**

Find a prediction threshold that maximizes recall with precision  $\geq 0.80$ : **0.7891**



## True Positive

Predicted demo  $\leq$  48 months

Address ID = 6196036

- Captures from **2009** to **2022**
- Demo date: **2024-08-20**
- Days to demolition (from last): **719**
- Model score: **0.945** ( $>0.7891$ )



## True Positive

Predicted demo  $\leq$  48 months

Address ID = 6196036

- Captures from **2009** to **2022**
- Demo date: **2024-08-20**
- Days to demolition (from last): **719**
- Model score: **0.945** ( $>0.7891$ )
- Post-demo photo: **2025-03-01**



## False Positive

Predicted demo  $\leq$  48 months

Address ID = 6828690

- Captures from **2009** to **2013**
- Demo date: **2018-05-10**
- Days to demolition (from last): **1743**
- Model score: **0.898** ( $>0.7891$ )



**1) Start: 2009-09-01**

## False Positive

Predicted demo  $\leq$  48 months

Address ID = 6828690

- Captures from **2009** to **2013**
- Demo date: **2018-05-10**
- Days to demolition (from last): **1743**
- Model score: **0.898** ( $>0.7891$ )
- Post-demo photo: **2018-07-01**



# Façade Model Performance

Metrics Threshold = 0.7891, n=2440	
Accuracy	85.7% (Base rate = 28.7%)
Precision	82.1%
Recall	64.1%
F1	0.72

	Predicted		PR-AUC	0.83
Actual	Positive	Negative	AUROC	0.95
Positive	TP: 449 (18.4%)	FN: 251 (10.3%)	Brier (replay aggregate)	0.1
Negative	FP: 98 (4.0%)	TN: 1642 (67.3%)	ECE (replay aggregate)	0.07

# User Interface

# User Interface

The screenshot displays a web application interface with two main sections: "Locations" and "Selected Item Preview".

**Locations:** This section features a map with a red location marker. A tooltip box over the marker displays the following information:

- Item ID: 132
- determination=Not likely soon (48m: 32%)

**Selected Item Preview:** This section provides details for the selected item:

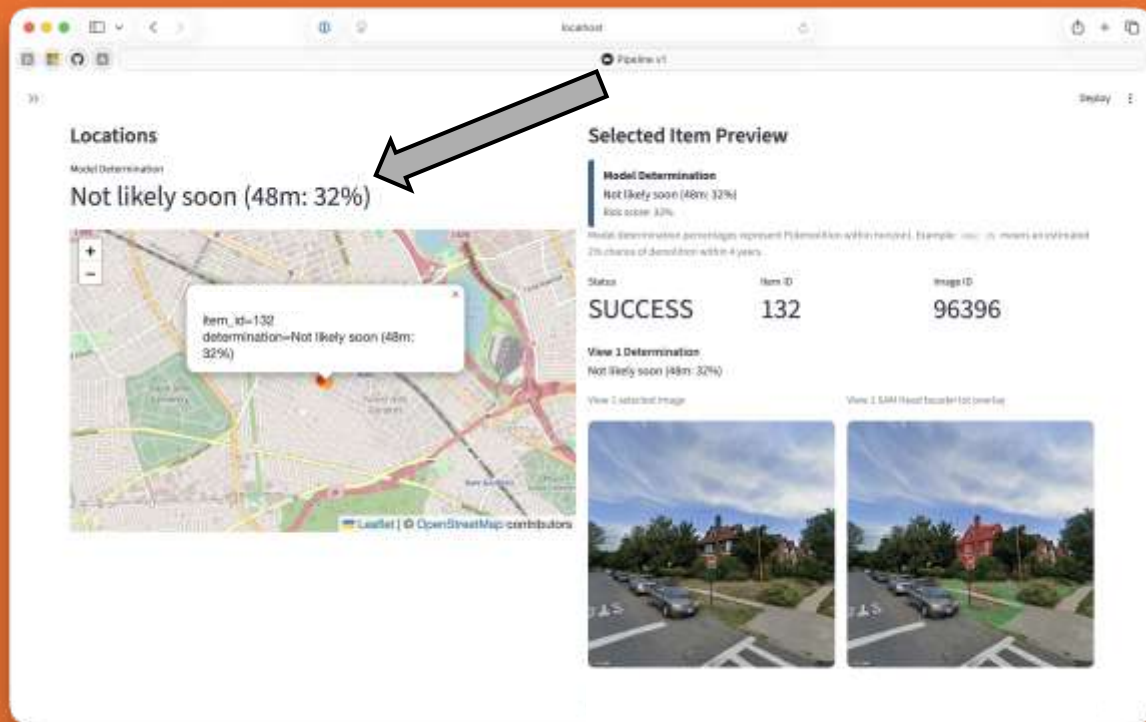
- Model Determination:** Not likely soon (48m: 32%) with a Risk score of 33%.
- Status:** SUCCESS
- Item ID:** 132
- Image ID:** 96396

Below the status information, there are two image thumbnails:

- View 1 Determination:** Not likely soon (48m: 32%)
- View 1 Selected Image:** A street-level view of a residential area.
- View 1 SAM Heatmap for (one file):** A corresponding SAM heatmap overlaid on the street view.

At the bottom left of the interface, there is a "Reveal Labs" logo.

# User Interface



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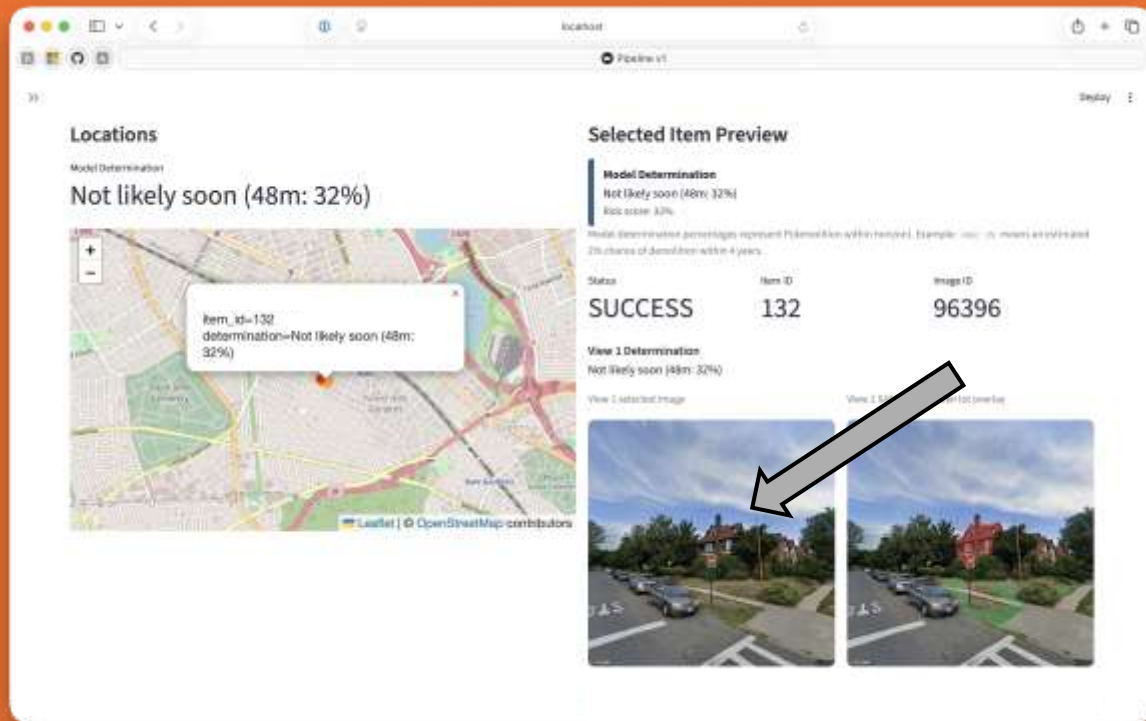
**Locations Section:**

- Model Determination: Not likely soon (48m: 32%)
- A map showing a city street grid with a red location marker. A tooltip box is overlaid on the map, containing the text: "Item\_id=132", "determination=Not likely soon (48m: 32%)". A large grey arrow points from the left towards this tooltip.

**Selected Item Preview Section:**

- Model Determination: Not likely soon (48m: 32%) (Risk score: 32%)
- Model Determination percentages represent the model's confidence in the result. Example: 32% means an estimated 29% chance of demolition within 4 years.
- Status: SUCCESS
- Item ID: 132
- Image ID: 96396
- View 1 Determination: Not likely soon (48m: 32%)
- View 1 selected image: [Image of a street scene]
- View 1 SAM Heatmap for lot (overlay): [Image of the same street scene with a heatmap overlay]

# User Interface



# User Interface

The screenshot displays a web application interface with two main sections: "Locations" and "Selected Item Preview".

**Locations:** This section features a map with a red location marker. A tooltip box is overlaid on the map, containing the text: "Item\_id=132", "determination=Not likely soon (48m: 32%)". Above the map, the text reads "Model Determination" and "Not likely soon (48m: 32%)".

**Selected Item Preview:** This section provides details for the selected item. It includes a "Model Determination" section with the text "Not likely soon (48m: 32%)". Below this, a table displays the following information:

Status	Item ID	Image ID
SUCCESS	132	96396

Below the table, there are two image thumbnails. The left thumbnail is labeled "View 1 Determination" and "Not likely soon (48m: 32%)". The right thumbnail is labeled "View 1 SAM Heatmap for (see Fig)". A large grey arrow points from the "View 1 Determination" text to the right image thumbnail.

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# 6

Project goal revisited,  
considerations, and  
future steps

# Goal Revisited: Stage 2

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Aim: Demonstrate an approach that outputs demolition risk of residential homes using façade imagery for survey address review

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Acquire façade imagery of residential demolitions

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✓ Acquire façade imagery of residential demolitions

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Aim: Demonstrate an approach that outputs demolition risk of residential homes using façade imagery for survey address review

✓ Acquire façade imagery of residential demolitions

Mask images to identify address in image

# Goal Revisited: Stage 2

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- ✓ Acquire façade imagery of residential demolitions
- ✓ Mask images to identify address in image

# Goal Revisited: Stage 2

Aim: Demonstrate an approach that outputs demolition risk of residential homes using façade imagery for survey address review

✓ Acquire façade imagery of residential demolitions

✓ Mask images to identify address in image

Train model on image + mask data to learn demolition patterns in imagery

# Goal Revisited: Stage 2

Aim: Demonstrate an approach that outputs demolition risk of residential homes using façade imagery for survey address review

- ✓ Acquire façade imagery of residential demolitions
- ✓ Mask images to identify address in image
- ✓ Train model on image + mask data to learn demolition patterns in imagery

# Considerations

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Privacy

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Imagery sourcing, licensing, and limitations

# Model: Where do we go from here?

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Expand predictions to more cities and shorter timescales:

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- 24-month

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Expand predictions to more cities and shorter timescales:

- 24-month, 12-month

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# Model: Where do we go from here?

Expand predictions to more cities and shorter timescales:

- 24-month, 12-month, 6-month

More prediction outputs:

# Model: Where do we go from here?

Expand predictions to more cities and shorter timescales:

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More prediction outputs:

- Residential vs. Commercial

# Model: Where do we go from here?

Expand predictions to more cities and shorter timescales:

- 24-month, 12-month, 6-month

More prediction outputs:

- Residential vs. Commercial
- Number of dwelling units

# Model: Where do we go from here?

Expand predictions to more cities and shorter timescales:

- 24-month, 12-month, 6-month

More prediction outputs:

- Residential vs. Commercial
- Number of dwelling units
- Building feature analysis

# Use Cases: Where do we go from here?

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Implementations:

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## Implementations:

- Occupied or abandoned residences
- Rate of new-home construction

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## Implementations:

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- Types of dwelling unit (single-family, multi-family, mixed-use)
- How many people live in a dwelling unit

# Use Cases: Where do we go from here?

## Implementations:

- Occupied or abandoned residences
- Rate of new-home construction
- Types of dwelling unit (single-family, multi-family, mixed-use)
- How many people live in a dwelling unit
- Residential blight rate
- Neighborhood health
- Housing trends

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## Implementations:

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- Rate of new-home construction
- Types of dwelling unit (single-family, multi-family, mixed-use)
- How many people live in a dwelling unit
- Residential blight rate
- Neighborhood health
- Housing trends
- ...!

# Thank You

RevealGC.com

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samuel.alter@tbmus.com

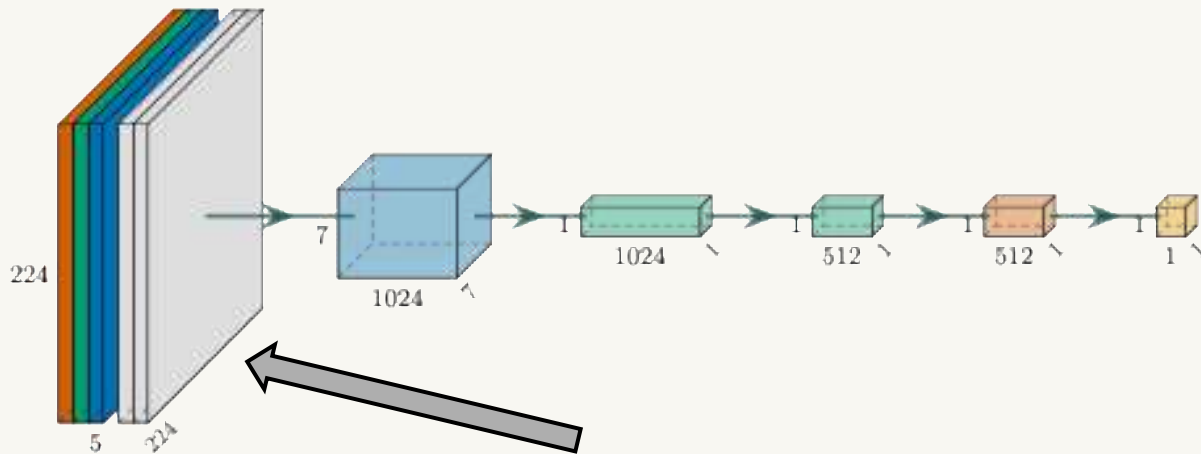
LinkedIn: in/yezzi-lee  
angi.lee@revealgc.com

LinkedIn: in/taylorjameswilson  
taylor.wilson@revealgc.com

LinkedIn: in/hectorferronato  
hector.ferronato@revealgc.com



# Methodology – 4. ConvNeXt Model

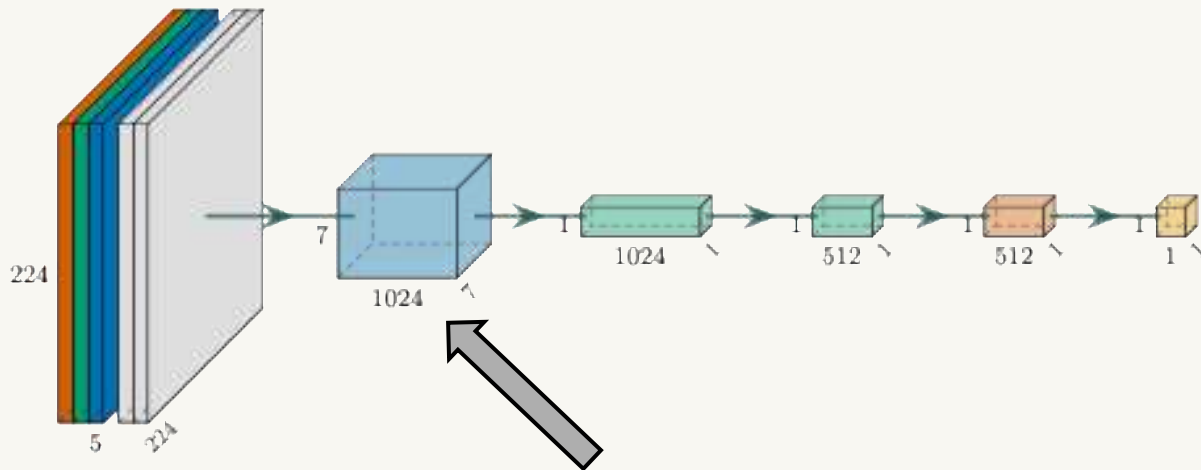


**Input 5-channel sequence of images:**

3-channel image (RGB) and 2-channel mask (Façade + Lot)

4x5x224x224

# Methodology – 4. ConvNeXt Model

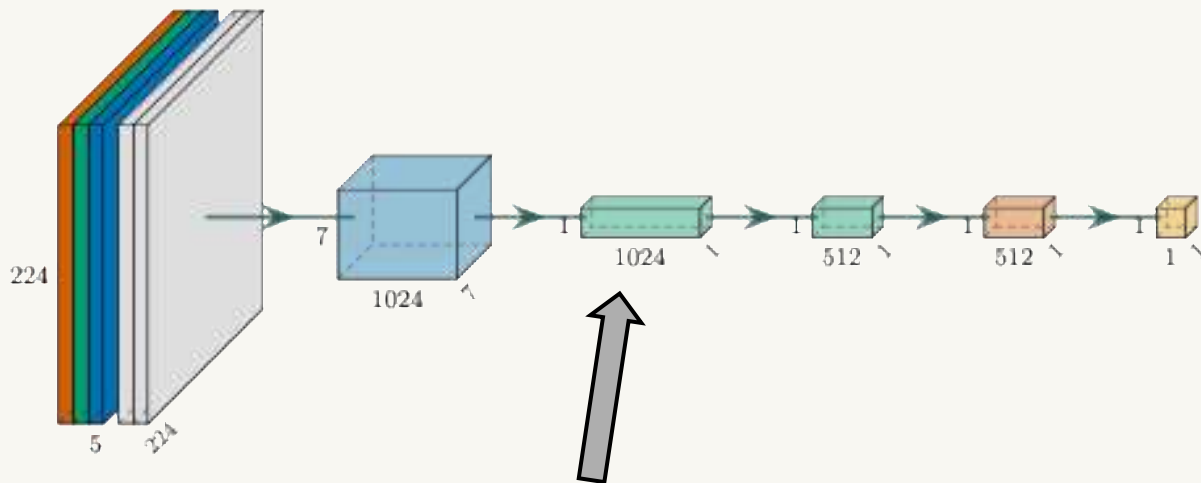


## 4-stage ConvNeXt Spatial Encoder:

Extract abstract features while downsampling resolution

$4 \times 224 \times 224 \times 5 \rightarrow \rightarrow 4 \times 7 \times 7 \times 1024$

# Methodology – 4. ConvNeXt Model

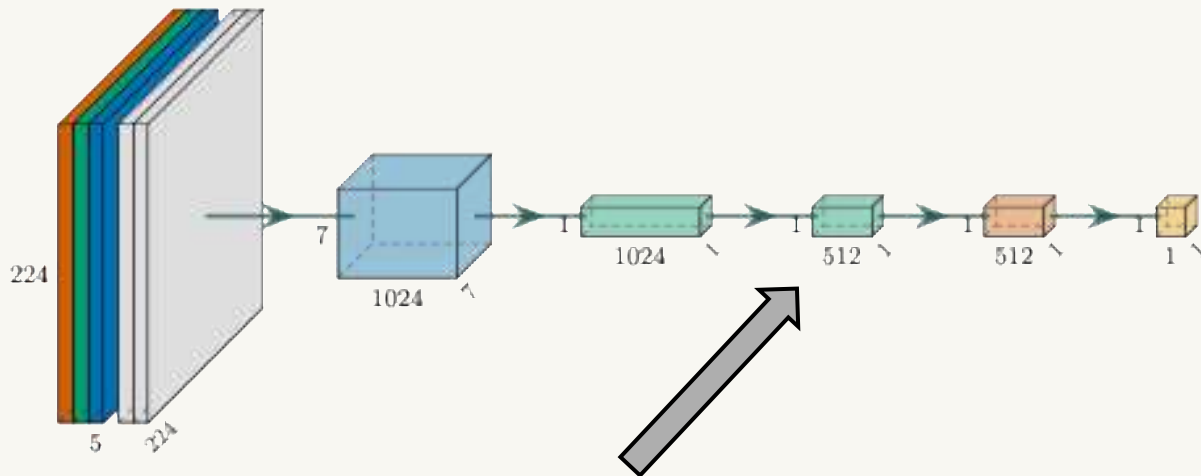


## Global Average Pooling:

Summarizes each image into a single vector

$4 \times 7 \times 7 \times 1024 \rightarrow 4 \times 1 \times 1 \times 1024$

# Methodology – 4. ConvNeXt Model

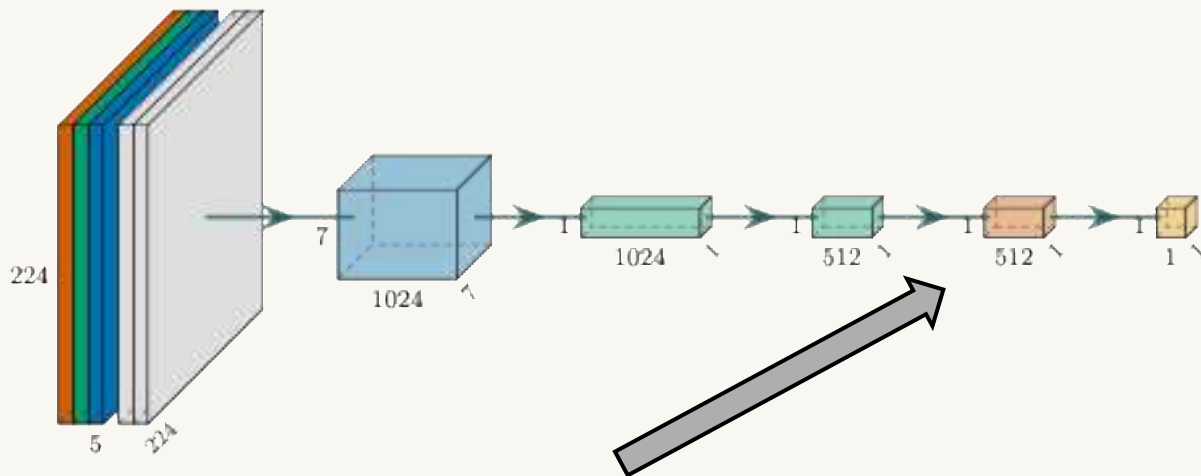


**Temporal Metadata:**

days\_since\_first

$4 \times 1 \times 1 \times 1024 \rightarrow 4 \times 1 \times 1 \times 512$

# Methodology – 4. ConvNeXt Model

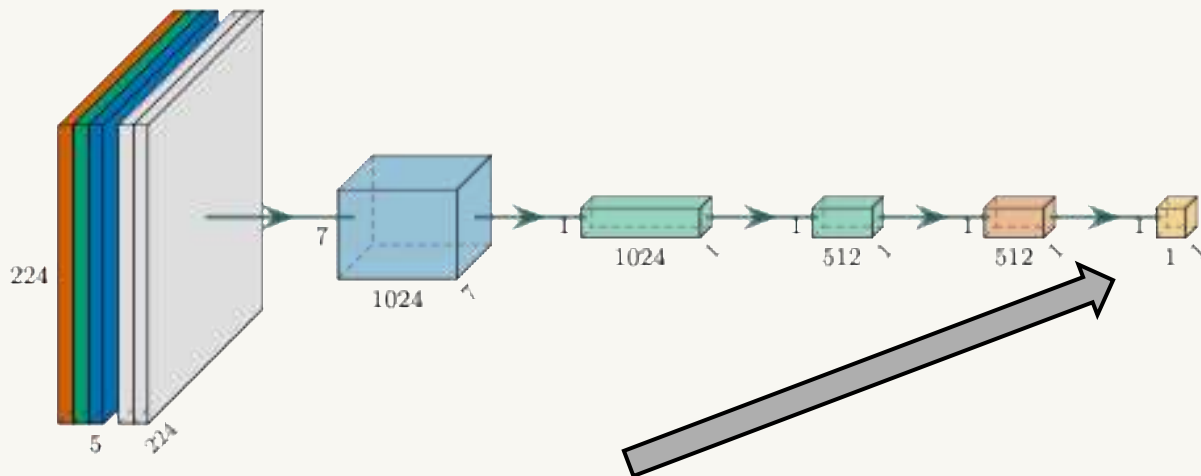


## Transformer:

Uses self-attention to identify temporal trends

4x1x1x512

# Methodology – 4. ConvNeXt Model



## **Hazard Head (48-month demolition risk):**

Converts summarized temporal features into single probability

$$4 \times 1 \times 1 \times 512 \rightarrow 1 \times 1 \times 1 \times 1$$

# SAM Head Performance

Overall Metrics	
test_mean_iou	0.6973
test_iou_facade	0.6863
test_iou_lot	0.4979
n_test_samples	102

Metrics – Façade		Metrics – Lot	
Precision	82.15%	Precision	61.51%
Recall	78.75%	Recall	84.83%
F1	80.42%	F1	71.31%

# SAM Head Performance – High IoU



Example Address (same as right image)



Example Address (same as left image)

# SAM Head Performance – High IoU



Ground Truth (i.e., Human-labeled)

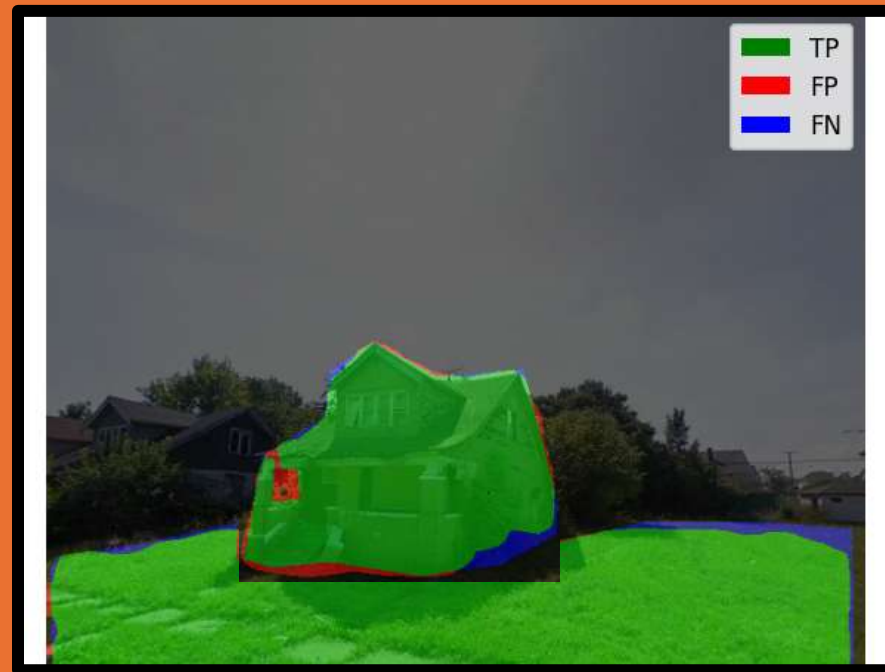


SAM Head Output (i.e., Machine-labeled)

# SAM Head Performance – High IoU



Ground Truth (i.e., Human-labeled)



SAM Head Output (i.e., Machine-labeled)

# SAM Head Performance – Low IoU

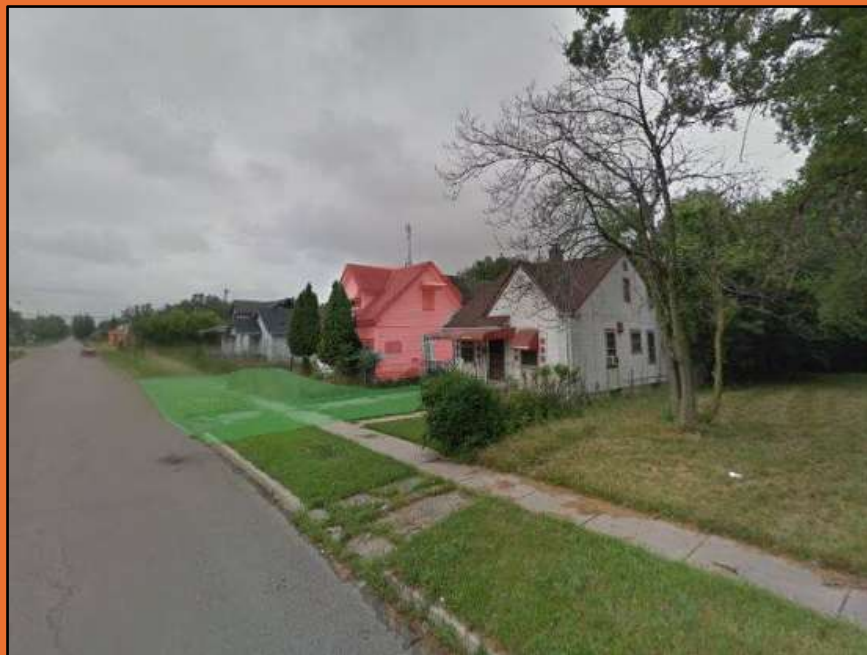


Example Address (same as right image)



Example Address (same as left image)

# SAM Head Performance – Low IoU

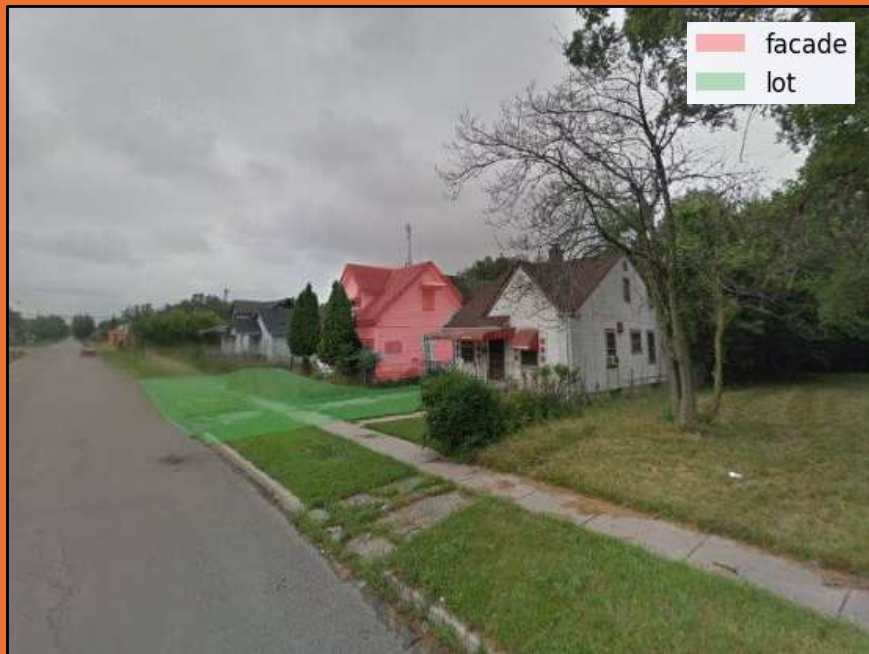


Ground Truth (i.e., Human-labeled)

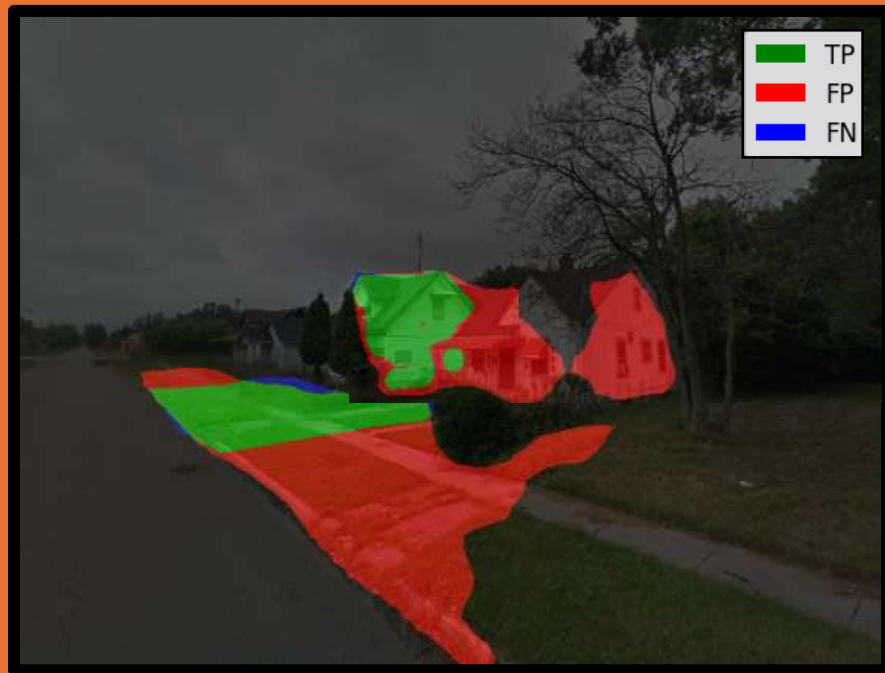


SAM Head Output (i.e., Machine-labeled)

# SAM Head Performance – Low IoU



Ground Truth (i.e., Human-labeled)



SAM Head Output (i.e., Machine-labeled)

Façade and Lot Mask Comparison with Ground-Truth

## True Negative

Predicted demo > 48 months

Address ID = 6033633

- Captures from **2007** to **2019**
- Demo date: **2024-02-20**
- Days to demolition (from last): **1725**
- Model score: **0.597** (<0.7891)



**1) Start: 2007-10-01**

## True Negative

Predicted demo > 48 months

Address ID = 6033633

- Captures from **2007** to **2019**
- Demo date: **2024-02-20**
- Days to demolition (from last): **1725**
- Model score: **0.597** (<0.7891)
- Post-demo photo unavailable



## False Negative

Predicted demo > 48 months

Address ID = 6022716

- Captures from **2009** to **2019**
- Demo date: **2019-08-16**
- Days to demolition (from last): **46**
- Model score: **0.572** (<0.7891)



**1) Start: 2009-07-07**

## False Negative

Predicted demo > 48 months

Address ID = 6022716

- Captures from **2009** to **2019**
- Demo date: **2019-08-16**
- Days to demolition (from last): **46**
- Model score: **0.572** (<0.7891)
- Post-demo photo: **2022-07-01**

