

December 12, 2024

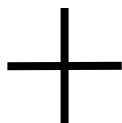
UC BERKELEY  
CAPSTONE 210  
FALL 2024

# SolarScape.AI

## Go for Solar

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Luis Cartagena, Alexandra Daniels, Nayan Ganguli, Jacob Jones, & Saurabh Pattarkine



# OUR TEAM

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**Luis  
Cartagena**



**Alexandra  
Daniels**



**Nayan  
Ganguli**



**Jacob  
Jones**



**Saurabh  
Pattarkine**

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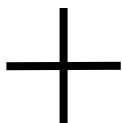
# PROBLEM \_\_\_\_\_

## **Solar Potential Uncertainty**

Difficulty in accurately assessing solar potential due to factors like roof obstructions and complex property layouts

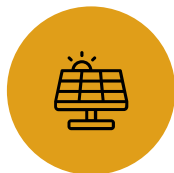
## **Limited Scalability**

Existing tools like *Google's Project Sunroof* often lack the scalability and accuracy needed for commercial and industrial applications



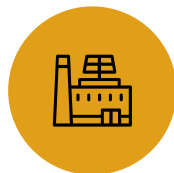
# MARKET OPPORTUNITY

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## Booming Market

Global solar market is projected to reach USD 436.36 billion by 2032\*



## Market Gap

Addresses the limitations of existing solutions and expands to commercial and industrial sectors



## Enhanced Accuracy

Surpasses Project Sunroof by accurately detecting roof obstructions (e.g. HVAC units), trees, open land, and parking lots

# INTERVIEWS WITH INDUSTRY EXPERTS

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Subject Matter Expert (SME)	Industry/Domain
Nicholas Brown	Utility Scale Solar and Wind Development
Chris Wheat	CEO - Policy & Government Affairs
Eugene Heimann	Large-Scale Solar Development
Matt O'Dell	Large Land Owner
Sanjay Singh	Machine Learning & Amazon Web Services
Emmanuel Bonsu	Software Engineer & Amazon Web Services
Vasha DuTell	UC Berkeley & MIT Computer Vision
Daniel, Katy, Benj, and Kate Jones	Recent Residential Solar Purchasers

# OUR TARGET USERS

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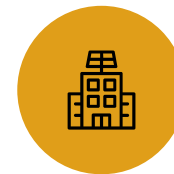
## New Mexico

Ranked 2nd for potential solar-generated electric power production\*



## Residential

Homeowners interested in installing solar panels on their homes



## Businesses

Companies interested in offsetting operating costs and carbon emissions

# PRODUCT FEATURES

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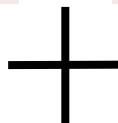
## Accurate Predictions

Calculate the solar energy potential of your commercial business or home



## Financial Analysis

Summarize cost savings and break-even point



## Rooftop Obstruction Detection

Identify objects that may block sunlight or complicate equipment installation



## Viability Assessment

Determine the feasibility of adopting solar





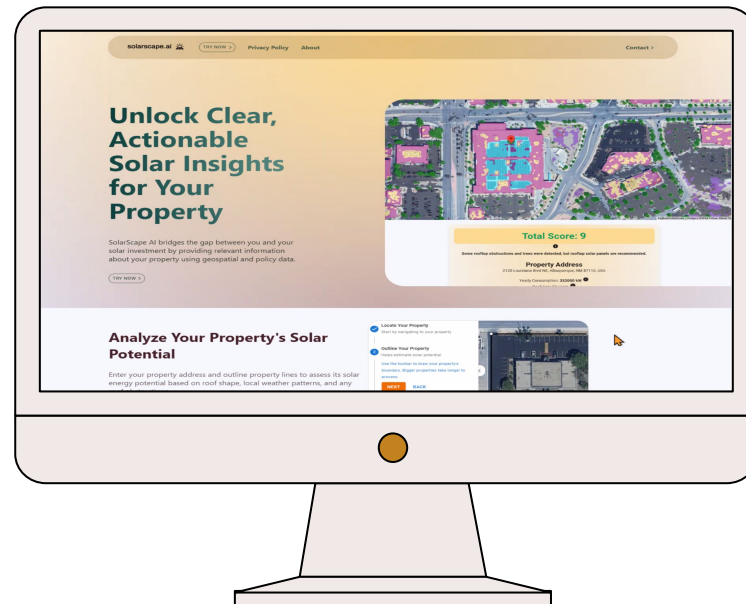
# OUR MISSION

Empowering businesses and communities  
with intelligent solar solutions powered by  
advanced computer vision.



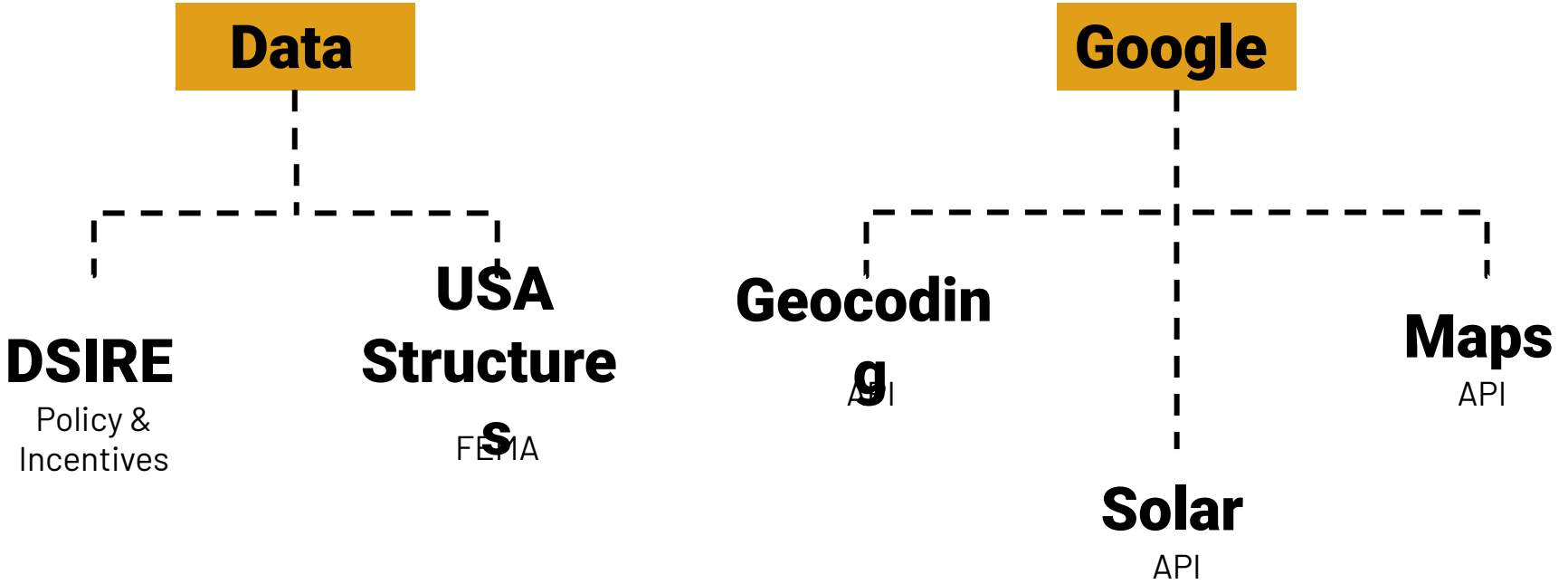
# PRODUCT DEMO

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# DATASETS & APIs

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# GOOGLE API

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## Geocoding API

Converts the address into geographic coordinates



## Solar API

Evaluates the roof's solar potential energy

LatLngBox

SolarPotential

SizeAndSunshineStats

RoofSegmentSizeAndSunshineStats

SolarPanel

SolarPanelOrientation

SolarPanelConfig

RoofSegmentSummary

FinancialAnalysis

Money

FinancialDetails

### JSON representation

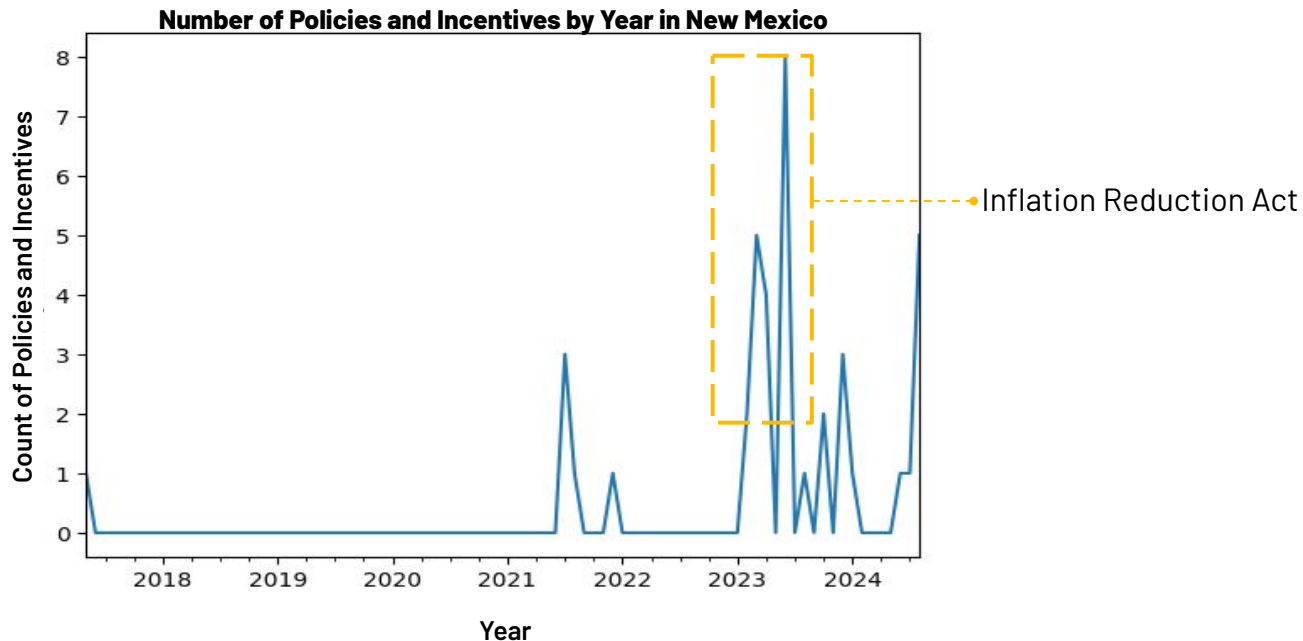
```
{
  "maxArrayPanelsCount": integer,
  "panelCapacityWatts": number,
  "panelHeightMeters": number,
  "panelWidthMeters": number,
  "panelLifetimeYears": integer,
  "maxArrayAreaMeters2": number,
  "maxSunshineHoursPerYear": number,
  "carbonOffsetFactorKgPerMwh": number,
  "wholeRoofStats": {
    object (SizeAndSunshineStats)
  },
  "buildingStats": {
    object (SizeAndSunshineStats)
  }
}
```

# DSIRE

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## 20+ years of incentives and policies that support energy efficiency and renewable energy

Focused on New Mexico's policy and incentive details

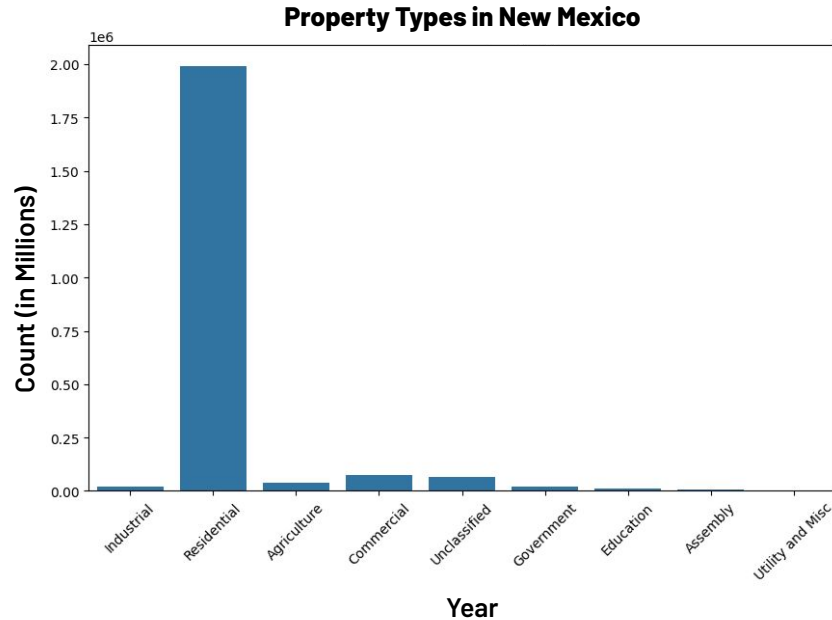


# USA STRUCTURES

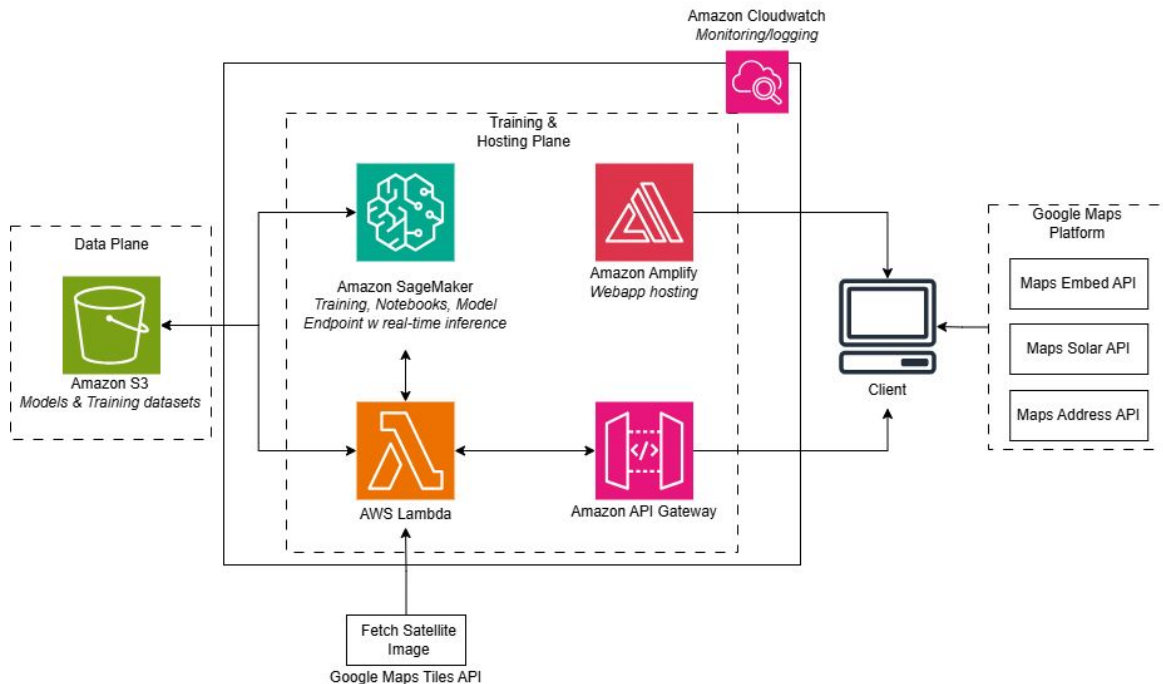
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**Footprints for all USA structures larger than 450 square feet; maintained by FEMA**

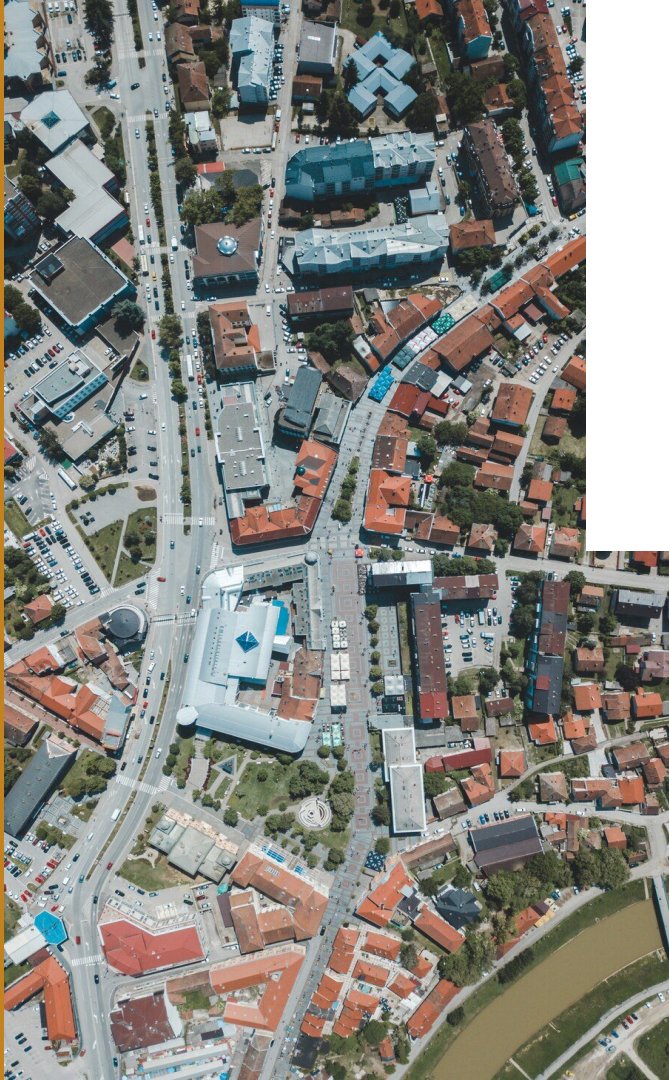
Focused on New Mexico's properties



# PRODUCT ARCHITECTURE & PIPELINE



Task	Tool/Service Used	Reason
Web app hosting	AWS Amplify	Ease of use
Web app (frontend)	React	Integration
CV model training & hosting	AWS Sagemaker, Lambda, API Gateway, Google Colab	Credits & ease of use
Data storage	Amazon S3	Credits & ease of use
Maps embed in browser	Google	Credits & ease of use



# MODELING APPROACH



Examine satellite images at the pixel level to capture fine-grained details and accurately identify rooftop obstructions and property boundaries



# GOOGLE MAPS API

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Randomly selected images across rural, residential and commercial areas in New Mexico



**Example Images**

**Image Size:** 1024x1024 Pixels

**Zoom Level:** 17

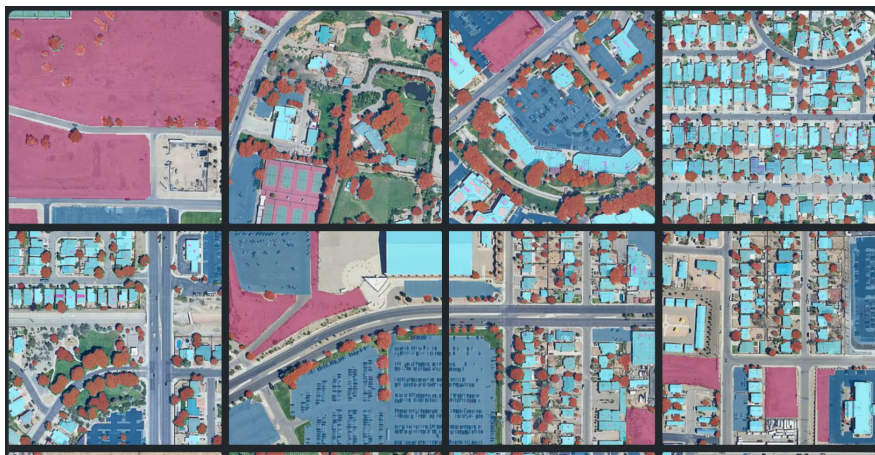
**Type:** RGB Composite Layers

# LABELBOX

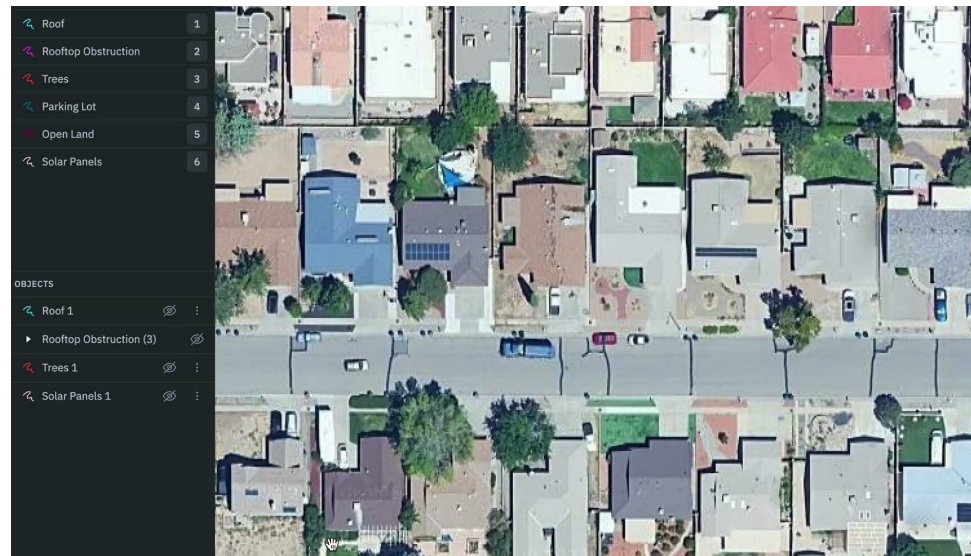
## Labeled 25 images for image segmentation

Each image had one labeler and one reviewer

**7 classes:** Background, Open Land, Parking Lot, Roof, Roof Obstruction, Solar Panel and Trees



Labeled Images



# IMAGE AUGMENTATION

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Increased images to 150

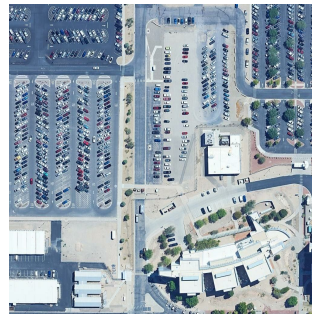
80% used for model training and 20% used for model validation



**Original**



**Horizontal  
Flip**



**Vertical Flip**



**90° Rotations**

# MODELS EXPLORED

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## YOLO

**Pros:** Fast Inference

**Cons:** Requires labels to fine-tune

**IOU Score:** 0.1572

**DICE Score:** 0.2541



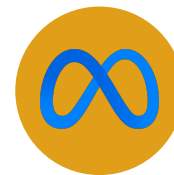
## STEGO

**Pros:** Self-Supervised Learning; no labels needed

**Cons:** Unresolvable Dependency Issues

**Val:** N/A

Final Model



## DINOv2

**Pros:** Self-Supervised Learning; not many labels needed to fine-tune; computationally efficient

**Cons:** Dependency Issues (resolvable!)

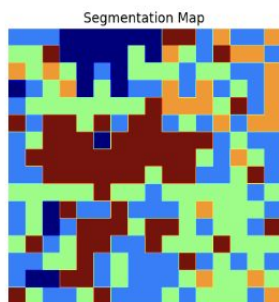
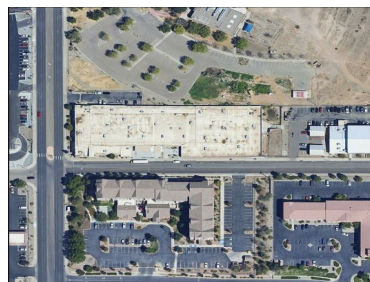
**IoU Score:** 0.4801

**DICE Score:** 0.5795



# EARLIEST DINOv2 RESULTS

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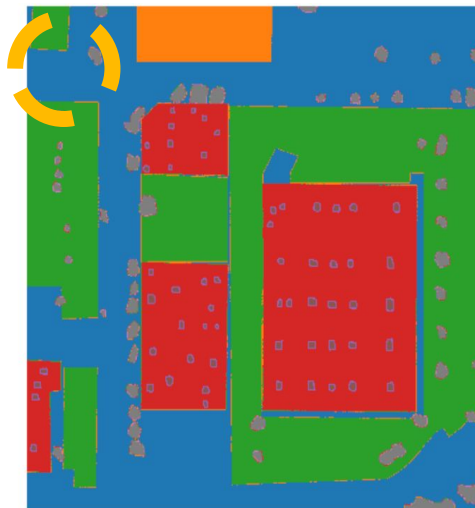
**DINOv2 Untrained**

# LATEST DINOv2 RESULTS

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Original



Training Data



Model Output

Legend:

- Background
- Trees
- **Open Land**
- Roof
- Parking Lot
- Rooftop
- Obstruction
- Solar Panels

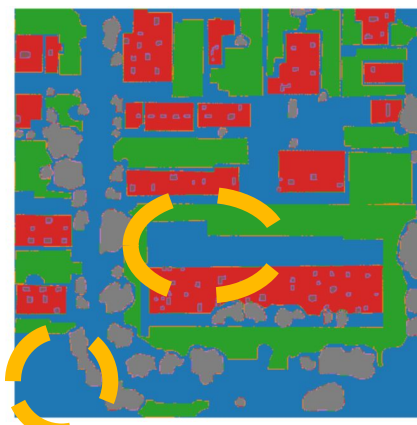
# DINOv2 LIMITATIONS

## Our training data is imperfect

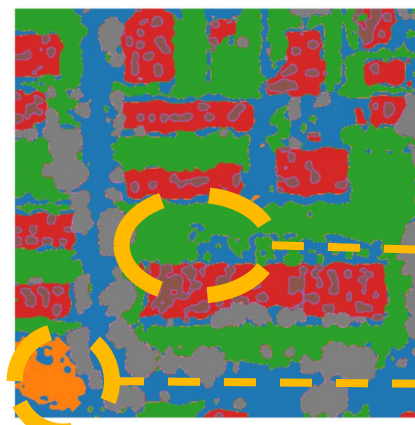
In this case, the model is picking up on potential open land that we did not identify



**Original**



**Training Data**



**Model Output**

### Legend:

- Background
- Trees
- **Open Land**
- Roof
- **Parking Lot**
- Rooftop
- Obstruction
- Solar Panels

—● Parking lot

—● Open Land

# DINOv2 LIMITATIONS

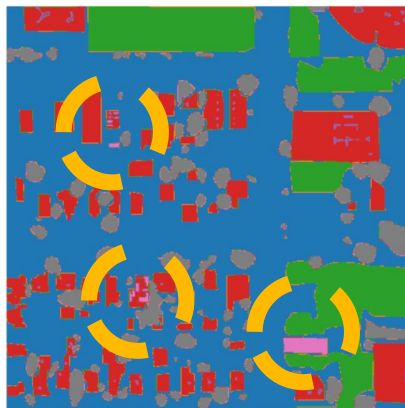
---

Existing solar panels made up only 0.19% of pixels in our training data (235k pixels)

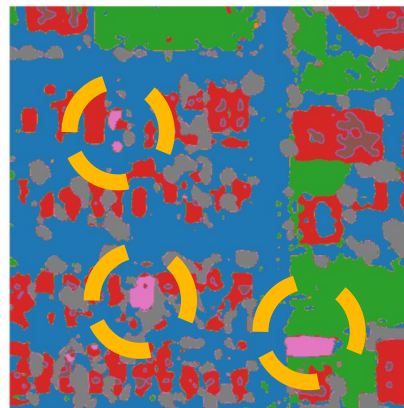
As a result, despite successful identification of solar panels, the shape can be unreliable



**Original**



**Training Data**



**Model Output**

Legend:

- Background
- Trees
- Open Land
- Roof
- Parking Lot
- Rooftop
- Obstruction
- **Solar Panels**



# DINOv2 LIMITATIONS

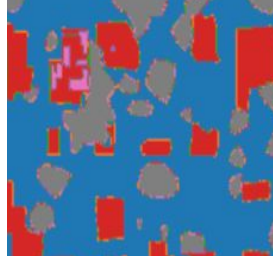
---

Existing solar panels made up only 0.19% of pixels in our training data (235k pixels)

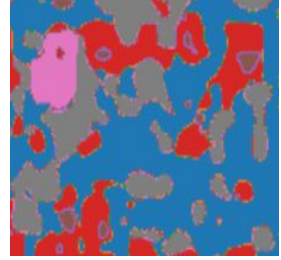
As a result, despite successful identification of solar panels, the shape can be unreliable



**Original**



**Training Data**



**Model Output**

Legend:

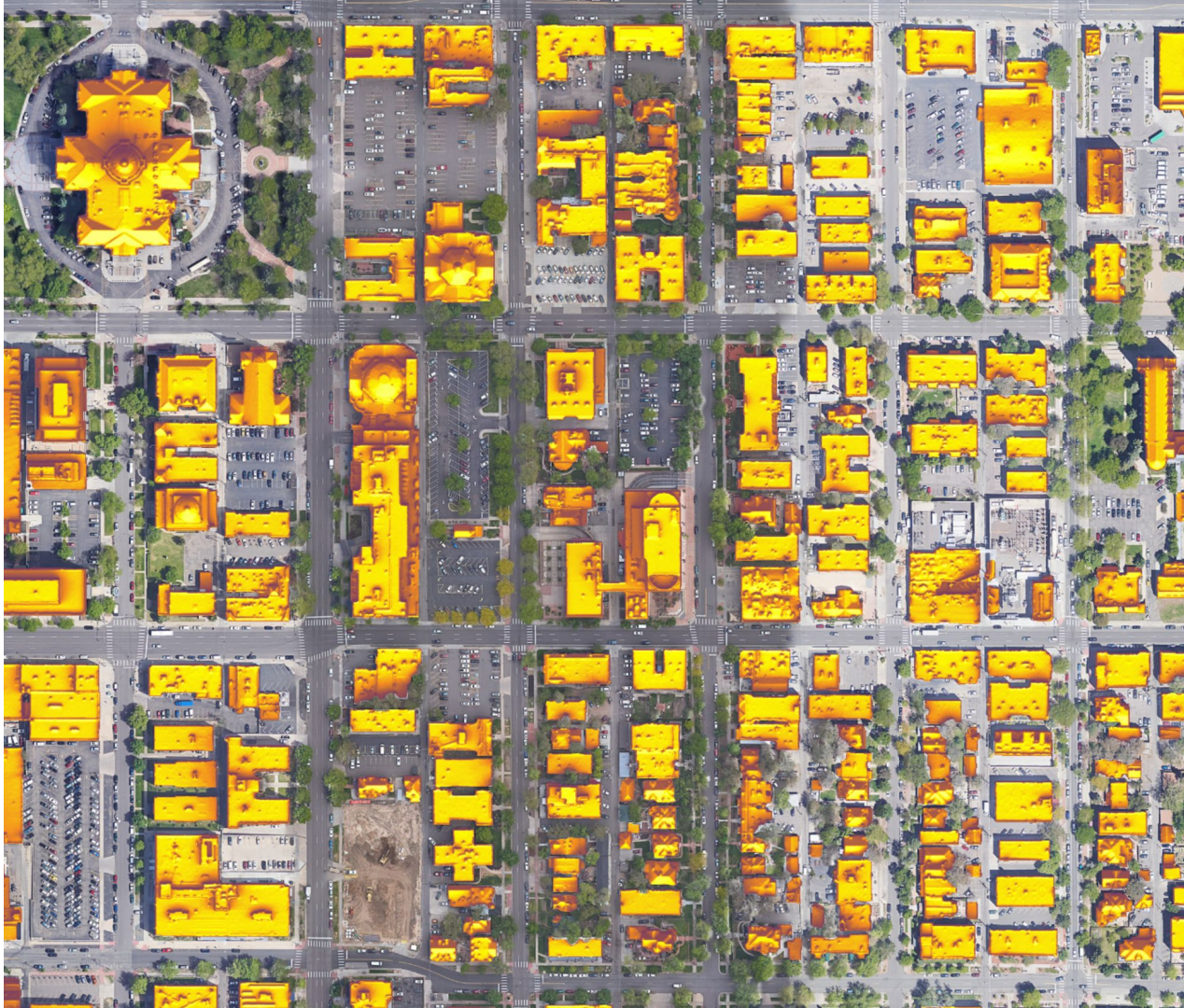
- Background
- Trees
- Open Land
- Roof

- Parking Lot
- Rooftop Obstruction
- **Solar Panels**

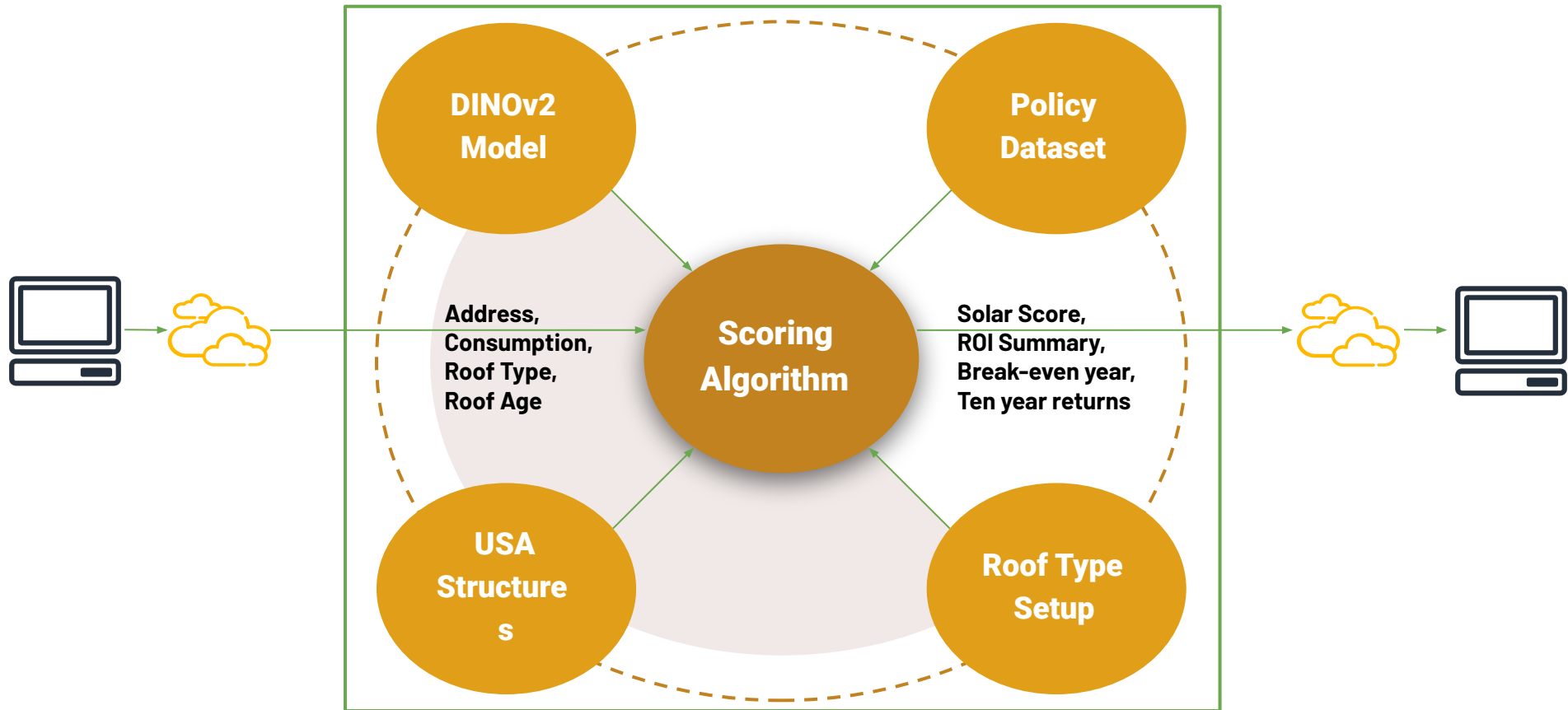
# DINOv2 LIMITATIONS

## Inference time

There is loading time associated with real time inference in the backend



# SCORING ALGORITHM



# SCORING ALGORITHM

Run Whole  
Image Through  
the Model



Whole Image  
(pixels):

0: 2650342,  
1: 186515,  
2: 1221964,  
3: 1031684,  
4: 215823,  
5: 29617,  
6: 206344,

Limit to Pixels  
in the  
Bounding Box



Bounding Box  
(pixels):

0: 2800,  
1: 1860,  
Roof: 1200,  
Obstruction: 60,  
4: 2150,  
5: 2960,  
6: 2100,

Run  
Calculations

```
units: "% (Pixels)"
thresholds:
  low:
    min: 0
    max: 10
  moderate:
    min: 11
    max: 25
  high:
    min: 26
    max: 100
simple_score:
  low: 2
  moderate: 1
  high: 0
```

Compute Results

Total Score: -

Recommendation not available.

Property Address

Address not provided.

Yearly Consumption: - kW

Roof Age: - years

Roof Type: -

Yearly ROI and Break-even Analysis



Break-even Point: Year 9

ROI (Return on Investment): The financial return achieved by investing in solar panels, calculated as the savings generated over time compared to the initial cost.

# TECHNICAL TAKEAWAYS

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## 01. Obstruction Detection

Image labeling and segmentation

## 03. Custom Scoring Algorithm

Makes product robust and scalable

## 02. Dynamic Property Bounds

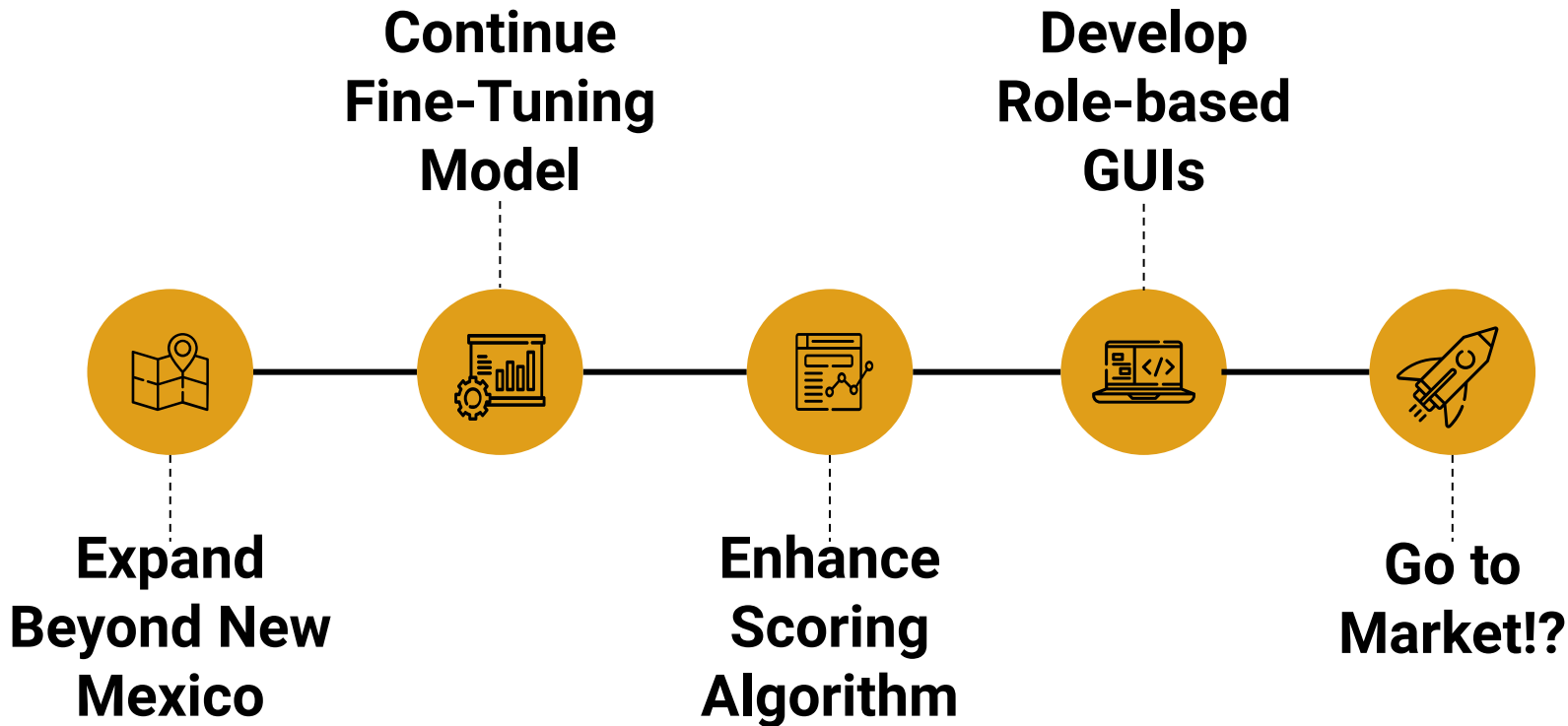
Images are selected at zoom level 17 to ensure obstruction are captured

## 04. AWS Architecture

Journey with Sagemaker

# OUR NEXT STEPS

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"I'd put my money on the sun and solar energy. What a source of power!"

**—Thomas Edison**





Appendix

# THANK YOU!

Joyce Shen & Korin Reid

Capstone 210 Section 7

SMEs:

Nicholas Brown

Chris Wheat

Eugene Heimann

Matt O'Dell

Sanjay Singh

Emmanuel Bonsu

Vasha DuTell

Daniel, Katy, Benj and Kate Jones

