ROB 498/599: Deep Learning for Robot Perception (DeepRob)

Lecture 14: Great Lakes Compute Resources;

(Previous) Final Project Showcase;

More on Robot Grasping

02/26/2025

https://deeprob.org/w25/

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Today

- Feedback and Recap (5min)
- Final Project Showcase (1hr)
- More on robot grasping (20min)
- Summary and Takeaways (5min)

Please sign up for final project teams at:
https://docs.google.com/spreadsheets/d/1FjWAjJ8p26xZmZaqsW4lew8H4iKe0FA78Q30eZ38g7A/edit?usp=sharing

Useful Links for Compute Resources

https://coerc.engin.umich.edu/intro-to-hpc/

- What is a cluster?
- Logging into a Cluster
- OpenOnDemand GUI access (interactive app - e.g., Jupyter Notebook)

All students enrolled should have received an email from Great Lakes.

$60.91 $\approx$ 371 GPU hours

Request placed in Queue. Depending on scheduler
Max time to request: two weeks (but may have to wait)

Useful Links for Compute Resources

Saving data:

- 60 days data purged (ARC will send reminder email. Be aware!)

- Saving data:

(498 or 599)

```
ls /scratch/rob498w25_class_root/rob498w25_class/YOUR_UNIQNAME
ls /scratch/rob498w25_class_root/rob498w25_class/shared_data
```

`my_accounts YOUR_UNIQNAME` (see your own account)

Your own folder

Shared data

```
sbatch python.sbat
```

Submit batch job

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Useful Links for Compute Resources

Submitting jobs:

```
sbatch python.sbat
```

Submit batch job, define time, job, etc.

(check out 2025/02/25 discussion recording for demo)

```
module keyword torch
module avail
module list
pip install numpy -user
module load python/3.10.4
```

#(currently loaded modules)

#(example)

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Useful Links for Compute Resources

Note about OpenOnDemand

there is a 'viz' partition in Great Lakes, that is only accessible form Open OnDemand:
https://documentation.its.umich.edu/arc-hpc/open-ondemand
It is set aside for interactive jobs and has a 2 hour wall clock limit. The nodes have NVIDIA Tesla P40 configured for accelerating OpenGL graphics using VirtualGL. This means that OpenGL application can get accelerated graphic with in the web interface.

Useful Links for Compute Resources

Transferring Data/Files (GLOBUS):

https://coerc.engin.umich.edu/globus/

Contact:

coe-research-computing@umich.edu
arc-support@umich.edu

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Useful Links for Compute Resources

Additional Slides on Great Lakes tutorial

https://docs.google.com/presentation/d/1_UyXAof8acyJ3nKCp8AkDRKArJNHwAJPufzJVvKjj08/edit?usp=sharing

W24 Project Showcase

(some previous examples
https://deeprob.org/w24/reports/)

Aha Slides (In-class participation)

https://ahaslides.com/81CWI

(Type in questions for our presenters - thanks!)

SolarCast-ML Presentation Schedule

Introduction

Background

Data Collection

Training

Future Work

Wrap-up

Cale Colony and Razan Andigani

Solarcast-ML Introduction

Project was a continuation of DeepRob W24 final project explorer multimodal model training

Proposed to extend a flagship model out of Google DeepMind

Implemented a custom data collection pipeline for gathering large amounts of data records over many months

Final training showed convergence on added outputs from base model

http://solarcast-ml.com/

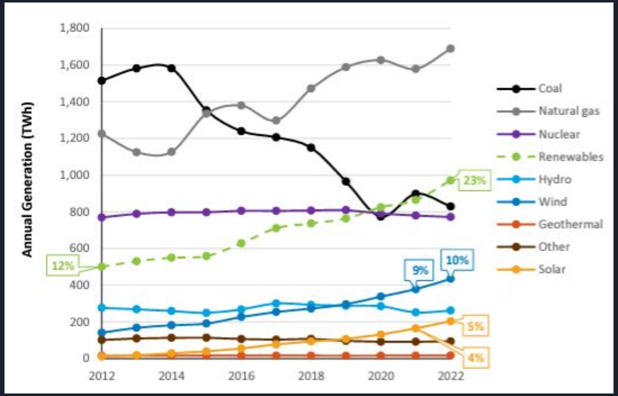
Solarcast-ML Background

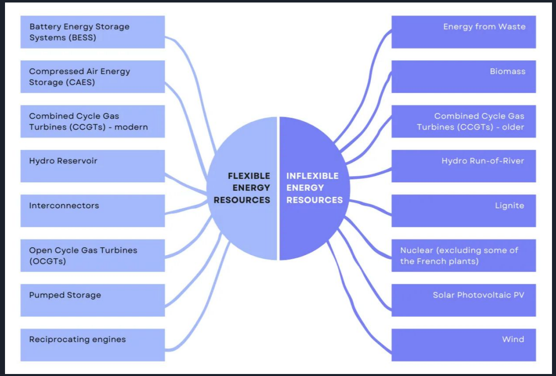
Solar production has provided an increasing amount of electricity production in the United States.

Traditional renewables (PV, wind, ROR Hydro) are brittle.

Intermittency causes a natural cap on integration levels into the power grid.

Excessive renewables present on the grid can cause negative wholesale prices coupled with in-feed tariffs.



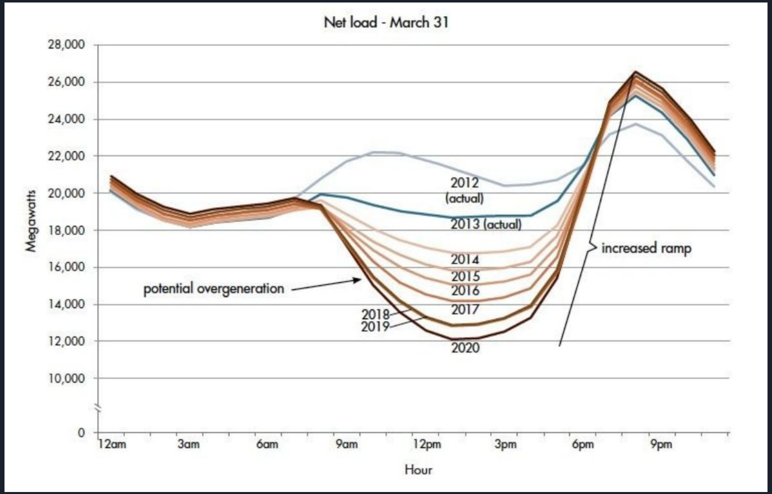


Solarcast-ML Background

The overproduction of PV electricity leads to a situation where net PV electrical demand leads to duck curve.

Peak production in middle of the day leads to curtailment.

Curtailment reduces/eliminates environmental benefits of marginal PV production.



Understanding the problems

01 Overproduction of PV causes negative wholesale prices and curtailment. Current strategies include storage (expensive), demand response programs, and reduction of incentives.

02 Intermittency necessitates extra spinning reserves (~10 min), supplemental (asynchronous) reserves (~10 min), and backup supplies (~60 min). Usually provided by combined cycle turbines, NG turbines, hydro, fossil ramp-up.

03 Renewables are primarily weather-related; economic dispatch models are a minute-to-minute, but weather forecasting is a 8-hour resolution.

Project objective

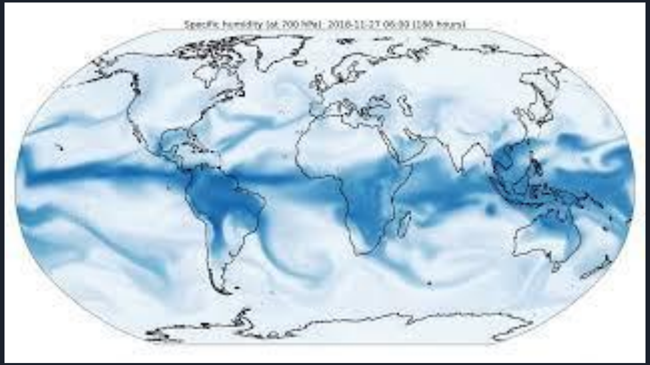
Explore the use of deep learning and multimodal AI models to facilitate renewable integration into power grid.

Related Work - GraphCast

GraphCast is the current SOTA weather forecasting model.

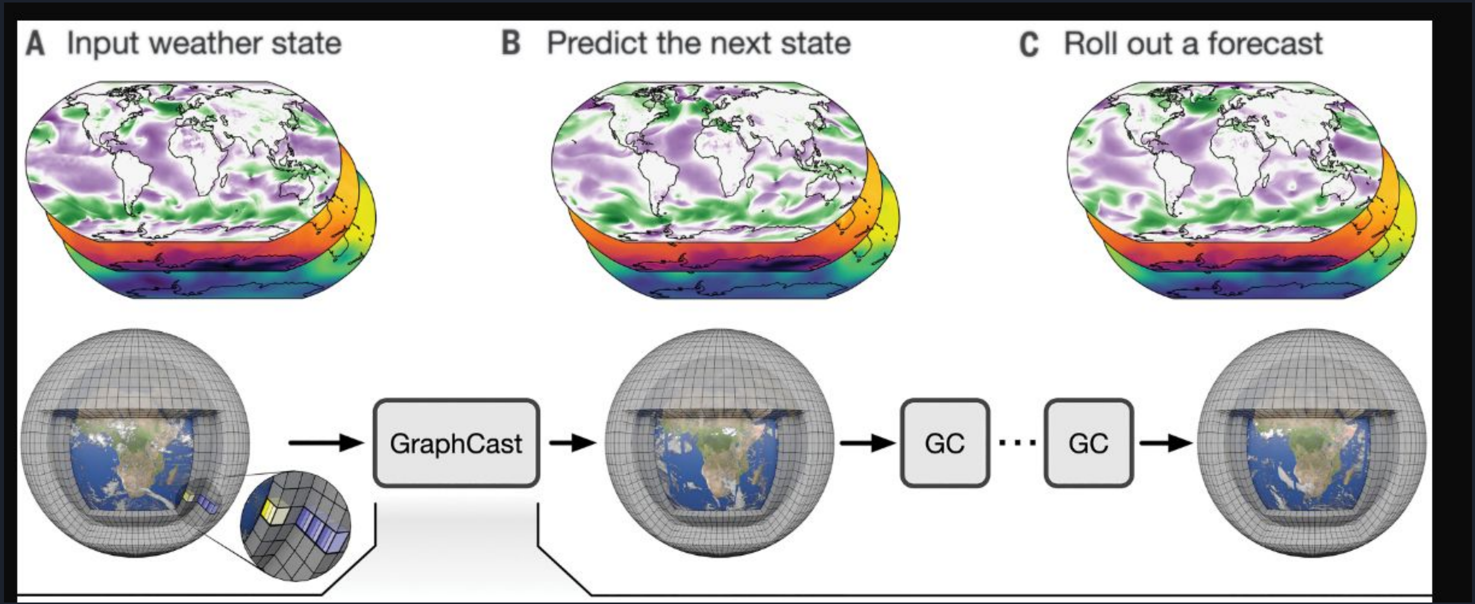
“Their predictions were more accurate than those of traditional weather models in 90% of tested cases and displayed better severe event prediction for tropical cyclones, atmospheric rivers, and extreme temperatures.”

GraphCast was training on 32 TPUv4 for approximately 4 weeks



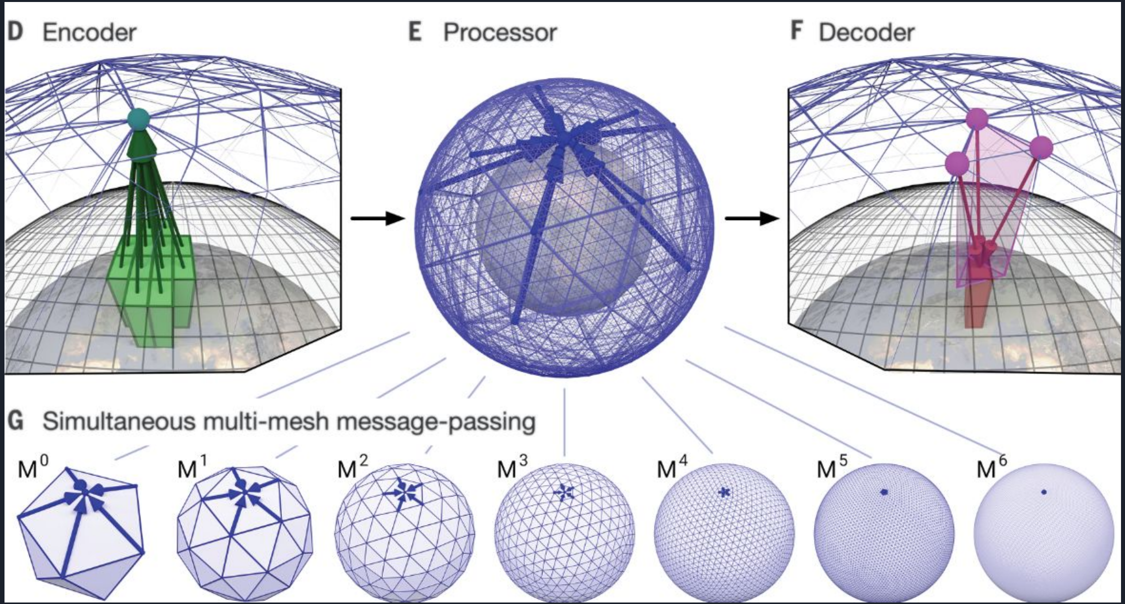
Related Work - GraphCast - Architecture

GraphCast is a GNN



Related Work - GraphCast - Architecture

GraphCast is a GNN



Related Work - GraphCast - Architecture

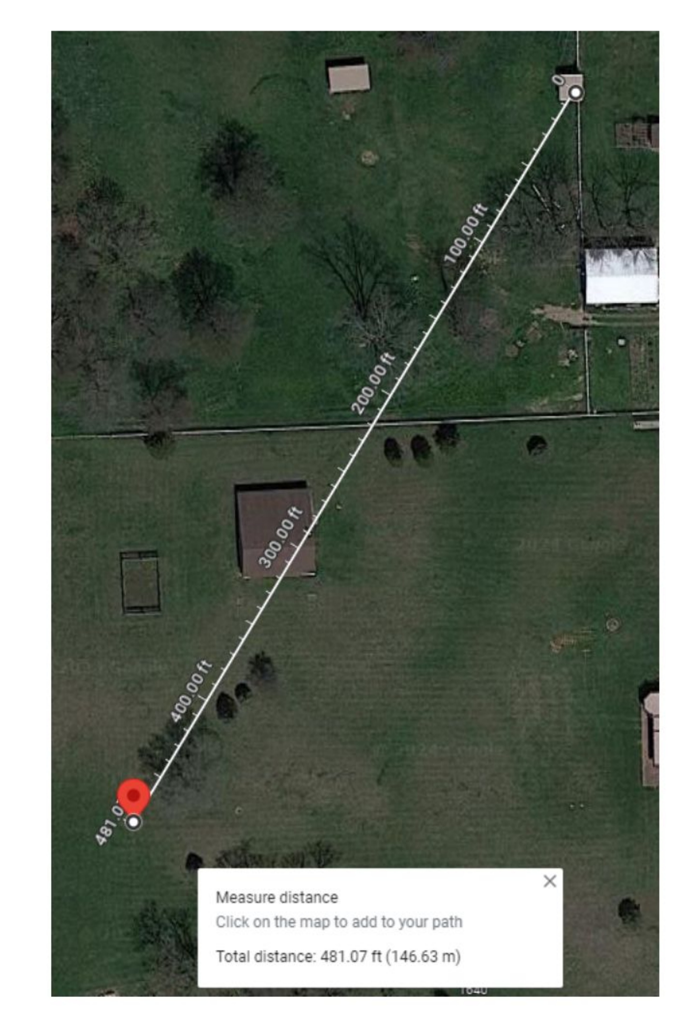
GNN dataset

Surface variables (5)	Atmospheric variables (6)	Pressure levels (37)
2-m temperature (*2T*)	**Temperature** (*T*)	1, 2, 3, 5, 7, 10, 20, 30, **50**, 70,
10-m u wind component (*10U*)	**U component of wind** (*U*)	**100**, 125, **150**, 175, **200**, 225,
10-m v wind component (*10V*)	**V component of wind** (*V*)	**250**, **300**, 350, **400**, 450, **500**,
Mean sea level pressure (*MSL*)	**Geopotential** (*Z*)	550, **600**, 650, **700**, 750, 775,
Total precipitation (*TP*)	**Specific humidity** (*Q*)	800, 825, **850**, 875, 900, **925**,
	Vertical wind speed (*W*)	950, 975, and **1000** hPa

Table 1. Weather variables and levels modeled by GraphCast.
The numbers in parentheses in the column headings are the number of entries in the column. Boldfaced variables and levels indicate those that were included in the scorecard evaluation. All atmospheric variables are represented at each of the pressure levels.

Node Distance

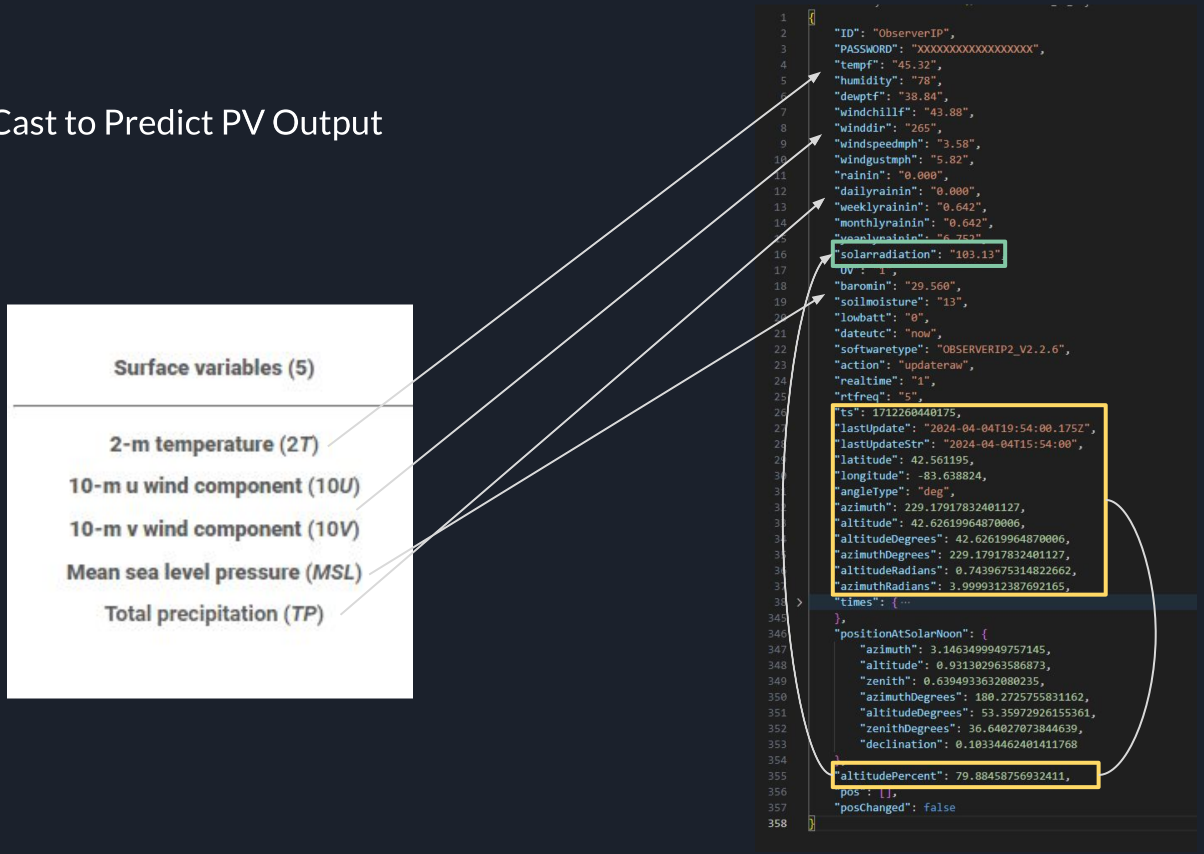
Distance from closest node to data collection device is approximately 481ft.



SolarCast-ML Methodology

Grand Strategy

Extend GraphCast to Predict PV Output



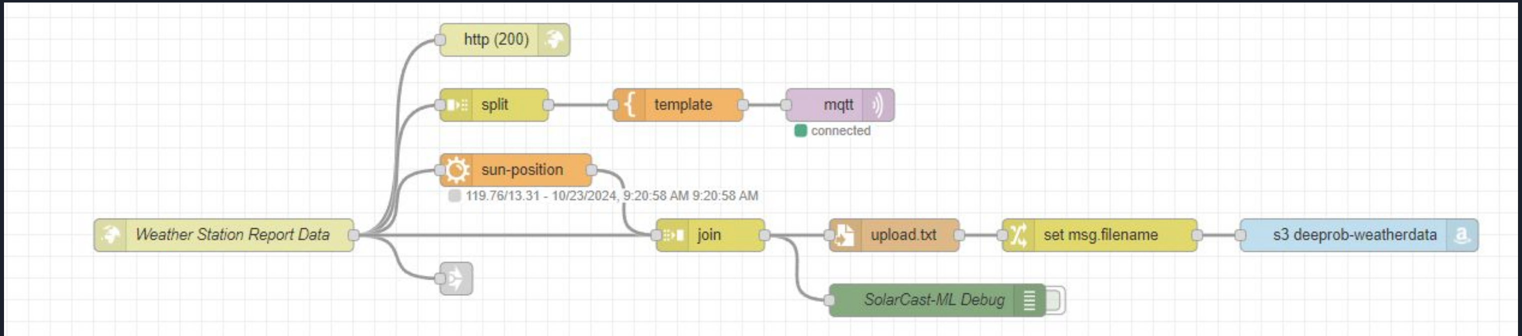
SolarCast-ML Data Collection

Data collection pipeline setup in Node-Red

Custom webserver collects update request from weather station

Sun position (altitude and azimuth) is calculated and added to the data record

Solar position is further refined into an incident angle and irradiance percentage

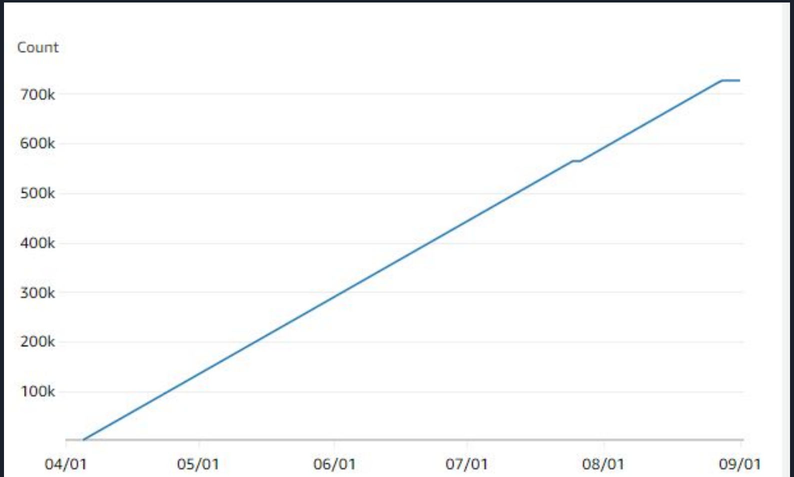


SolarCast-ML Data Collection Results

After record creation, record is formatted and prepared for upload to S3 research bucket

Data collection operated without issue (except for a power failure) for approximately months.

Total data collection yielded approximately 729,000 data records.



SolarCast-ML Additional Data

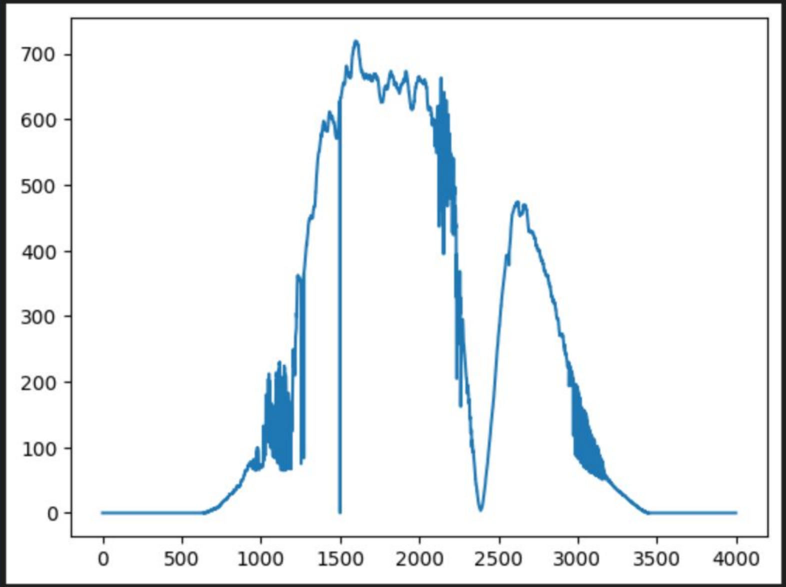
Also needed to include benchmark solar irradiance

Approximately 1.4kW/m^2

Used in modifying solar output percentage

SolarCast-ML Curiosity

What was the date of this data?



SolarCast-ML Model Setup

Tried several layouts of FCNs

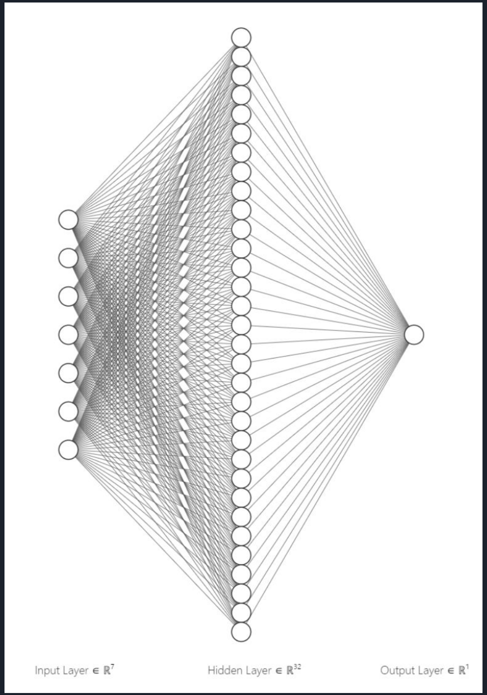
Ablations showed a single 32 node hidden layer worked best

Used ADAM for training

Training took minutes on a RTX4090

Input layer consisted of temperature, humidity, dew point, wind speed, rain, barometric pressure, and altitude percent

Output is an irradiance ratio of observed power vs total irradiance at perfect conditions



SolarCast-ML Model Results

Final convergence to around 40W per square meter (1400W at perfect irradiance)

Shows that given a node state, the proposed network can predict within 40W what the observed solar irradiance will be

Further information at http://solarcast-ml.com/

****** Results are per node ******

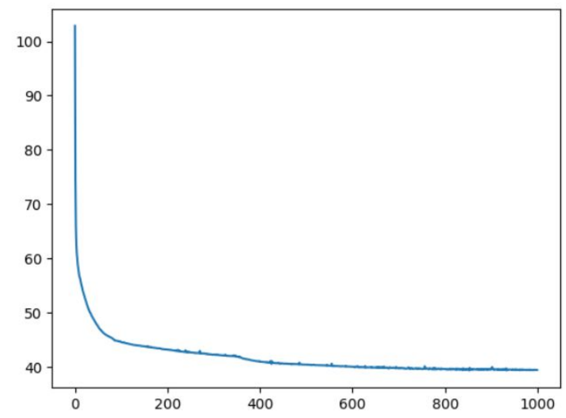


Fig. 5. Final convergence of the trained model over 1000 epochs, showing predicted solar radiation values. Y-axis is watts per square meter mean square training loss.

SolarCast-ML Discussion and Further Work

Run analysis comparing NOAA weather stations against GraphCast node states

Prepare integration model between GC node states (6-hours)

Check model accuracy against other nodes

Correlate between wind vector and wind output

Integrate the use of ERCOT data wider GC dataset

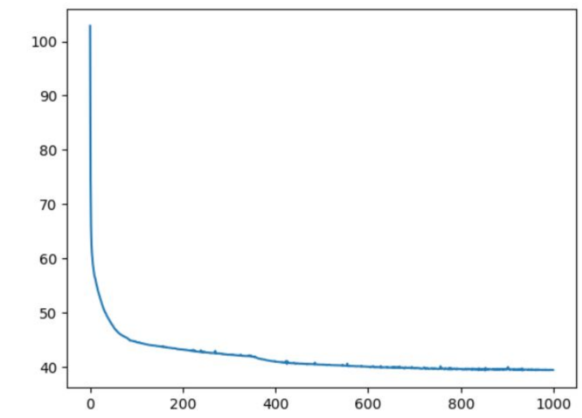


Fig. 5. Final convergence of the trained model over 1000 epochs, showing predicted solar radiation values. Y-axis is watts per square meter mean square training loss.

SolarCast-ML Acknowledgements

Thanks Razan! She provided a ton of help getting the project out the door in DeepRob.

Also thanks to Amazon

SORNet: Spatial Object-Centric Representations for Sequential Manipulation

Jace Aldrich, Ariana Verges Alicea, Hannah Ho

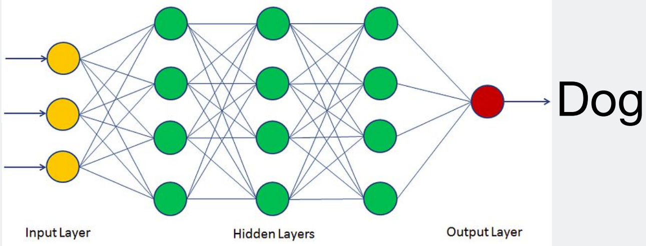
Original Paper Authors: Wentao Yuan, Chris Paxton, Karthik Desingh, Dieter Fox

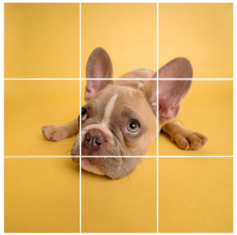
ROBOTICS

Why SORNet?

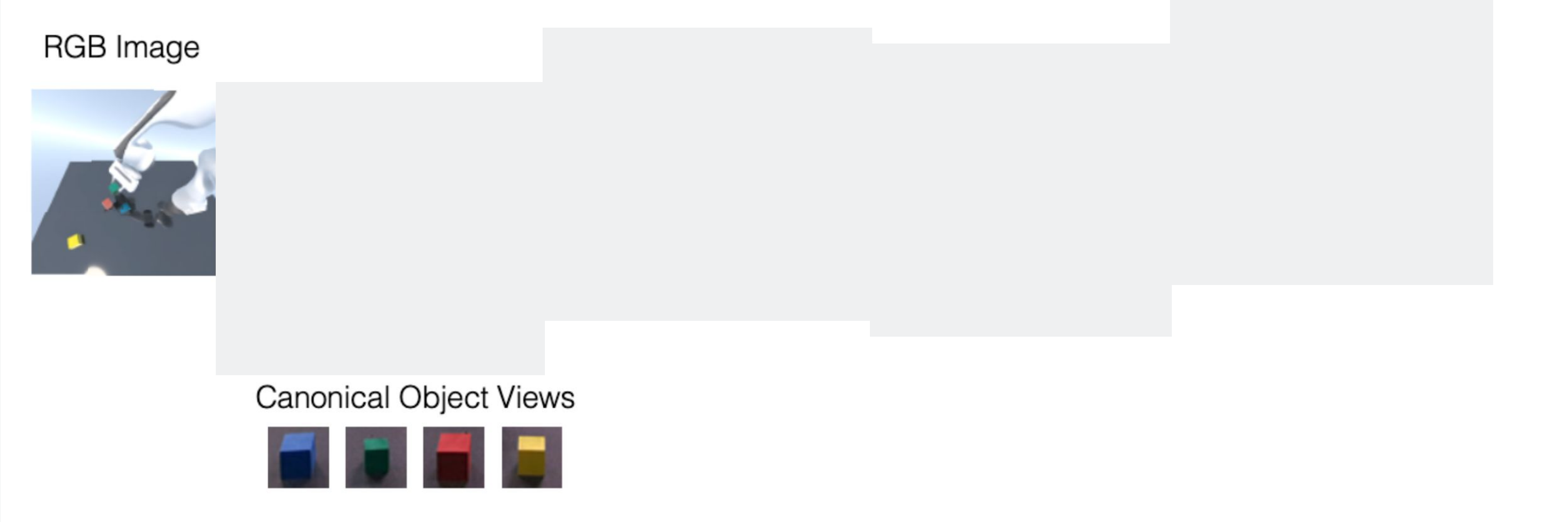
- How can we get information of objects and their spatial relationship with each other for object manipulation?
- With it, a robot can perform sequential tasks with objects (e.g. stacking blocks).

Vision Transformer Models





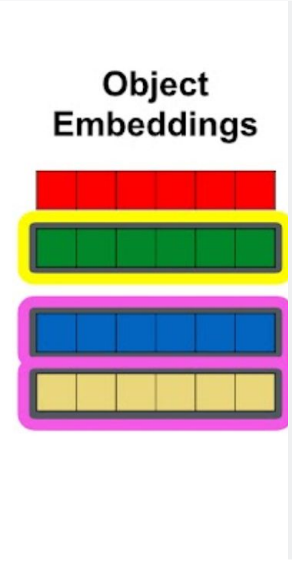
Overall Architecture



Object Embedding Network

RGB observation view 1 | RGB observation view 2 *(optional)* | Depth observation view x *(optional)*

Readout Networks



Leonardo Dataset

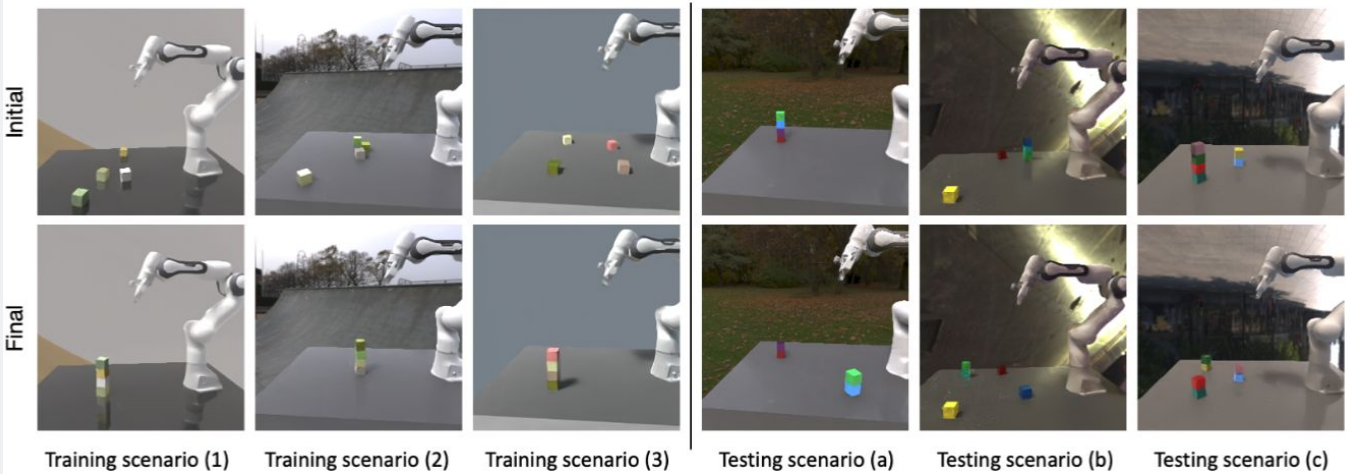
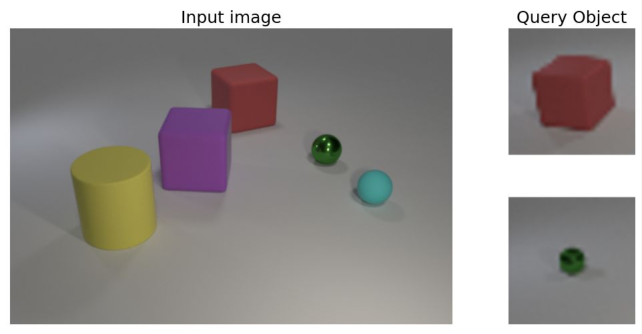


Figure 5: Sample scenes from training and testing scenarios in the Leonardo dataset. Top row shows the initial configuration of a sequence and the bottom row shows the goal configuration. The training scenarios contain 4 blocks with a single goal condition. The testing scenarios contain 4-7 blocks with heldout colors and various goal conditions involving multi-tower stacking.

Kitchen Dataset

Figure 6: Sample scenes from the kitchen dataset. The top and bottom rows show two different views. SORNet can leverage additional views to improve performance, but does not require multiple views.

Model Output



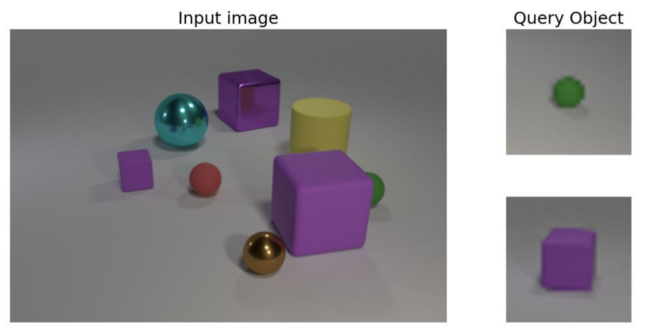
Question

Is the large red rubber cube to the left of the small green metal sphere?

Answer

SORNet: Yes

Ground truth: Yes



Question

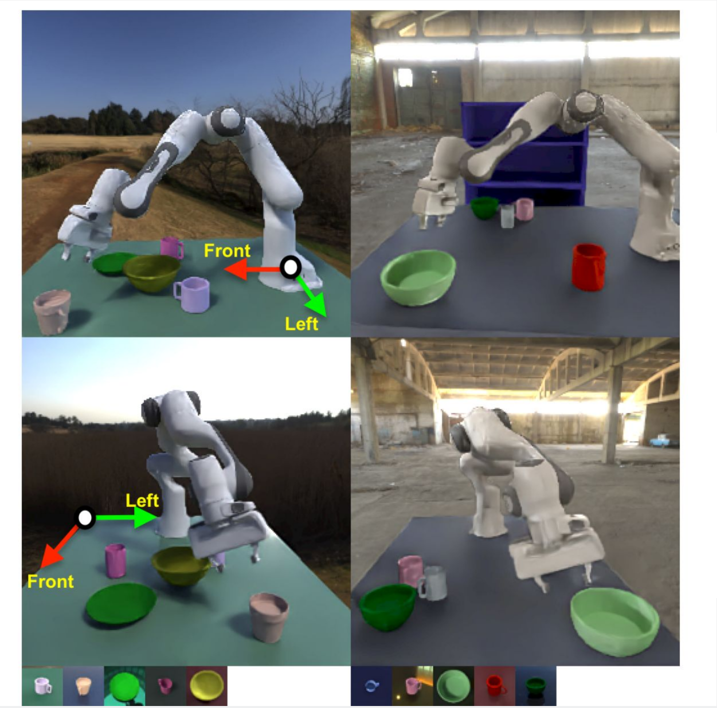
Is the small green rubber sphere to the right of the large purple rubber cube?

Answer

SORNet: Yes

Ground truth: Yes

Kitchen – Simulated



on_surface(00_pastel_purple_Mug, tabletop)
on_surface(01_pinkish_tan_Mug, tabletop)
on_surface(02_bottle_green_Bowl, tabletop)
on_surface(03_barbie_pink_Mug, tabletop)
on_surface(04_brownish_green_Bowl, tabletop)
left_of(01_pinkish_tan_Mug, 02_bottle_green_Bowl)
left_of(00_pastel_purple_Mug, 03_barbie_pink_Mug)
left_of(04_brownish_green_Bowl, 03_barbie_pink_Mug)
right_of(03_barbie_pink_Mug, 04_brownish_green_Bowl)
right_of(03_barbie_pink_Mug, 00_pastel_purple_Mug)
right_of(02_bottle_green_Bowl, 01_pinkish_tan_Mug)
in_front_of(02_bottle_green_Bowl, 03_barbie_pink_Mug)
in_front_of(01_pinkish_tan_Mug, 04_brownish_green_Bowl)
in_front_of(01_pinkish_tan_Mug, 00_pastel_purple_Mug)
behind(00_pastel_purple_Mug, 01_pinkish_tan_Mug)
behind(04_brownish_green_Bowl, 01_pinkish_tan_Mug)
behind(03_barbie_pink_Mug, 02_bottle_green_Bowl)
touching(02_bottle_green_Bowl, 04_brownish_green_Bowl)
touching(04_brownish_green_Bowl, 00_pastel_purple_Mug)
touching(00_pastel_purple_Mug, 04_brownish_green_Bowl)
touching(04_brownish_green_Bowl, 02_bottle_green_Bowl)

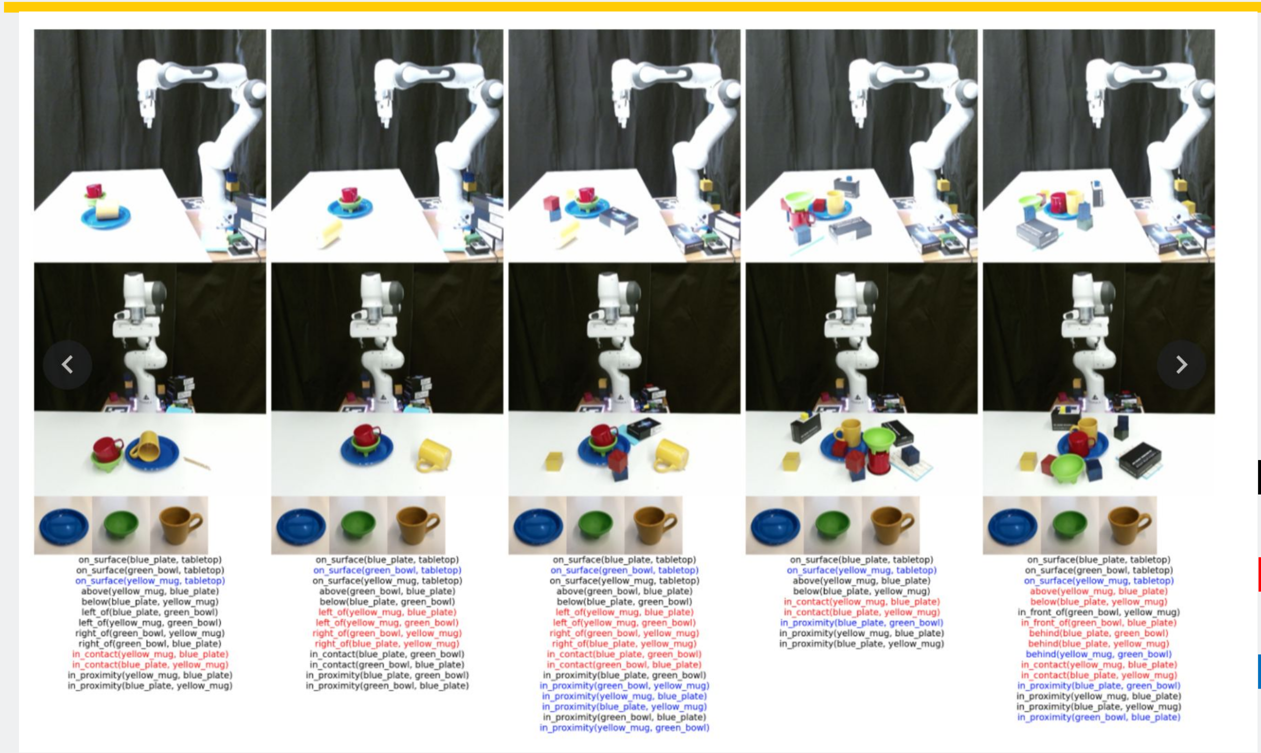
on_surface(00_baby_blue_Mug, tabletop)
on_surface(01_bubblegum_pink_Mug, tabletop)
on_surface(02_lightish_green_Bowl, tabletop)
on_surface(03_deep_red_Mug, tabletop)
on_surface(04_dark_forest_green_Bowl, tabletop)
left_of(02_lightish_green_Bowl, 04_dark_forest_green_Bowl)
left_of(02_lightish_green_Bowl, 00_baby_blue_Mug)
right_of(00_baby_blue_Mug, 02_lightish_green_Bowl)
right_of(04_dark_forest_green_Bowl, 02_lightish_green_Bowl)
in_front_of(02_lightish_green_Bowl, 03_deep_red_Mug)
in_front_of(04_dark_forest_green_Bowl, 01_bubblegum_pink_Mug)
behind(01_bubblegum_pink_Mug, 04_dark_forest_green_Bowl)
behind(03_deep_red_Mug, 02_lightish_green_Bowl)
touching(00_baby_blue_Mug, 01_bubblegum_pink_Mug)
touching(01_bubblegum_pink_Mug, 04_dark_forest_green_Bowl)
touching(04_dark_forest_green_Bowl, 00_baby_blue_Mug)
touching(00_baby_blue_Mug, 04_dark_forest_green_Bowl)
touching(04_dark_forest_green_Bowl, 01_bubblegum_pink_Mug)
touching(01_bubblegum_pink_Mug, 00_baby_blue_Mug)

Black – Correct

Red – False Negative

Blue – False Positive

Kitchen – Real World



Black – Correct

Red – False Negative

Blue – False Positive

PROPS Relation Dataset (Ours)

PROPS Relation Dataset (Ours)

Input image

Query Object

Question

Is the potted meat can

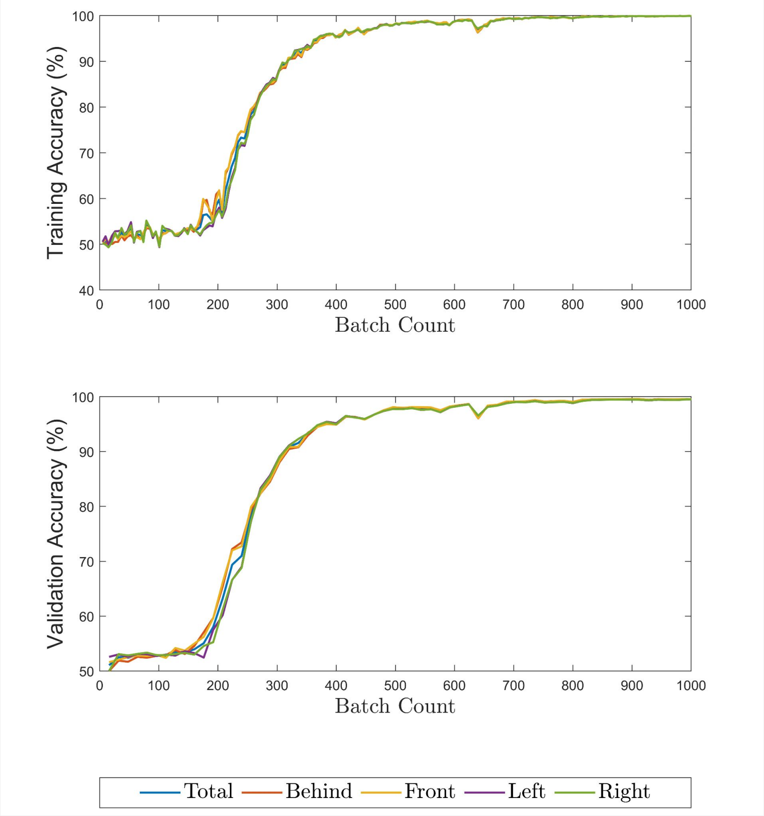
behind the master chef can?

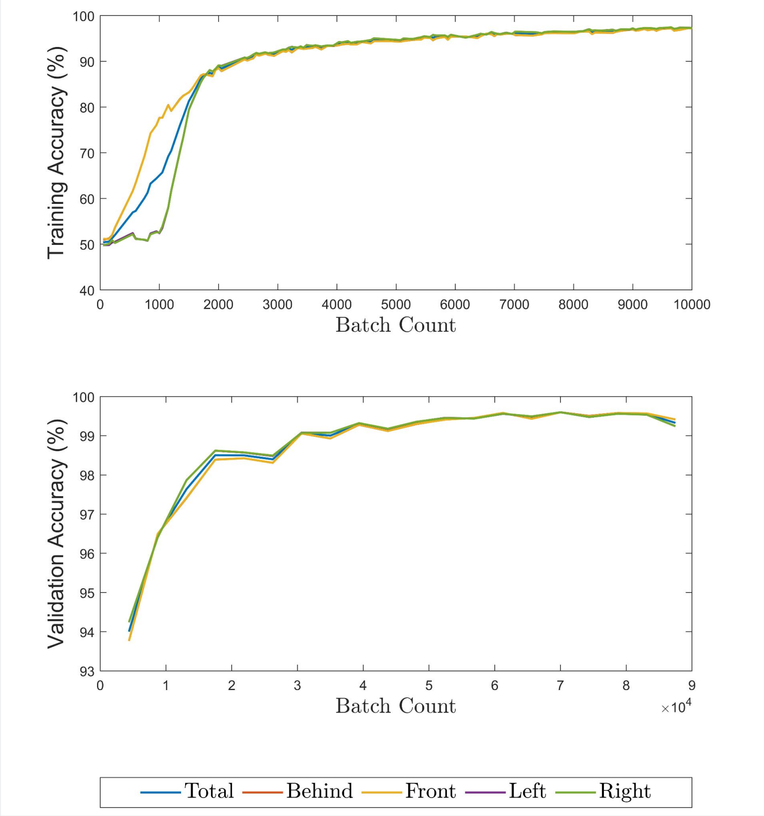
Answer

SORNet: Yes

Ground truth: Yes

CLEVR (left) vs PROPS (right)





PROPS Object Accuracy

	Master Chef Can	Cracker Box	Sugar Box	Tomato Soup Can	Mustard Bottle	Tuna Fish Can	Gelatin Box	Potted Meat Can	Mug	Large Marker	Average
Master Chef Can	-	99.30	99.77	98.80	98.90	98.77	98.65	99.20	99.15	98.85	99.04
Cracker Box	99.10	-	99.37	99.80	99.20	99.39	98.54	98.70	99.55	98.3000	99.11
Sugar Box	99.20	99.14	-	99.09	99.37	98.89	99.75	99.32	99.54	99.20	99.28
Tomato Soup Can	98.40	99.65	99.26	-	99.40	98.87	98.86	99.60	99.00	99.15	99.13
Mustard Bottle	99.30	98.90	99.26	99.90	-	98.87	99.68	98.95	98.55	98.95	99.15
Tuna Fish Can	98.98	99.28	99.41	98.98	97.95	-	99.11	99.13	98.98	99.28	99.01
Gelatin Box	99.19	99.40	99.88	99.51	99.89	99.33	-	98.81	99.78	99.03	99.43
Potted Meat Can	99.20	98.70	99.03	99.75	98.30	99.38	98.81	-	98.90	98.20	98.92
Mug	98.80	99.45	99.49	98.80	98.70	98.92	99.51	99.65	-	99.45	99.20
Large Marker	98.30	98.10	99.43	99.20	98.95	99.23	99.24	99.20	99.55	-	99.03
Average	98.94	99.10	99.43	99.31	98.96	99.08	99.13	99.17	99.22	98.93	99.13
Complete Average	98.99	99.10	99.36	99.22	99.06	99.04	99.28	99.05	99.21	98.98	

TABLE I: Full Size PROPS Data Validation Accuracy Percentages for all Relationships. The row is object 1 in the relationship, the column is object 2 in the relationship. The complete average is the average over the object's row and column, as SORNet treats the first and second patches differently.

Site Page Link

[Automatic Data Generation for SORNet: PROPS Relation Dataset | DeepRob: Deep Learning for Robot Perception]

Self-Supervised Learning for 6D Object Pose Estimation

Sydney Belt, Conghao Jin, Gurnoor Kaur, Joshua Symonds

Original Paper (Wild6D) Authors:

K. Zhang, Y. Fu, S. Borse, H. Cai, F. Porikli, X. Wang

ROBOTICS

Background

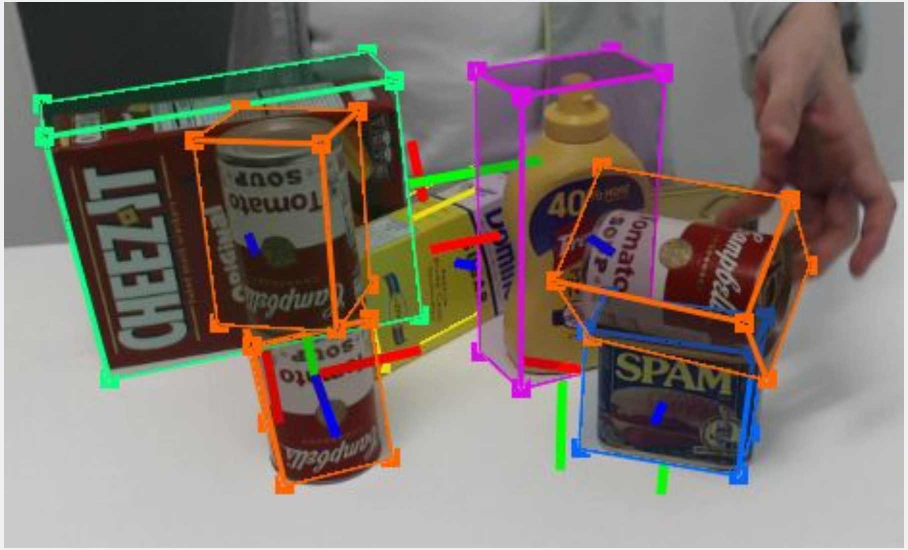
6D Object Pose Estimation

2D Images / Video Frames

3D Position

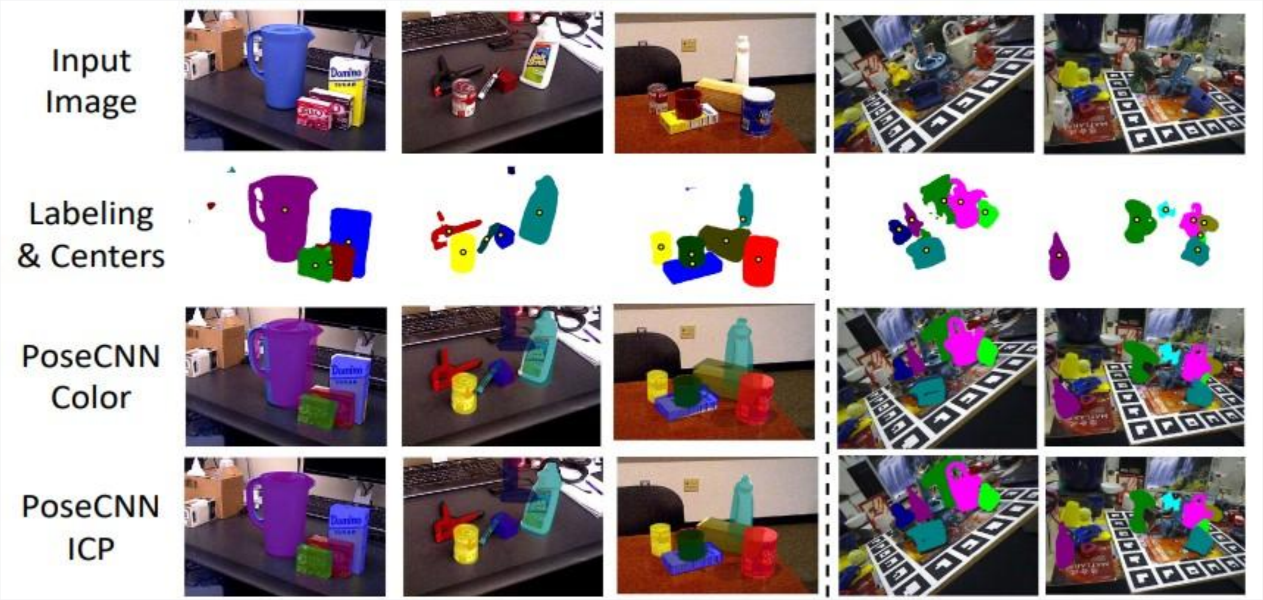
3D Orientation

6D Pose



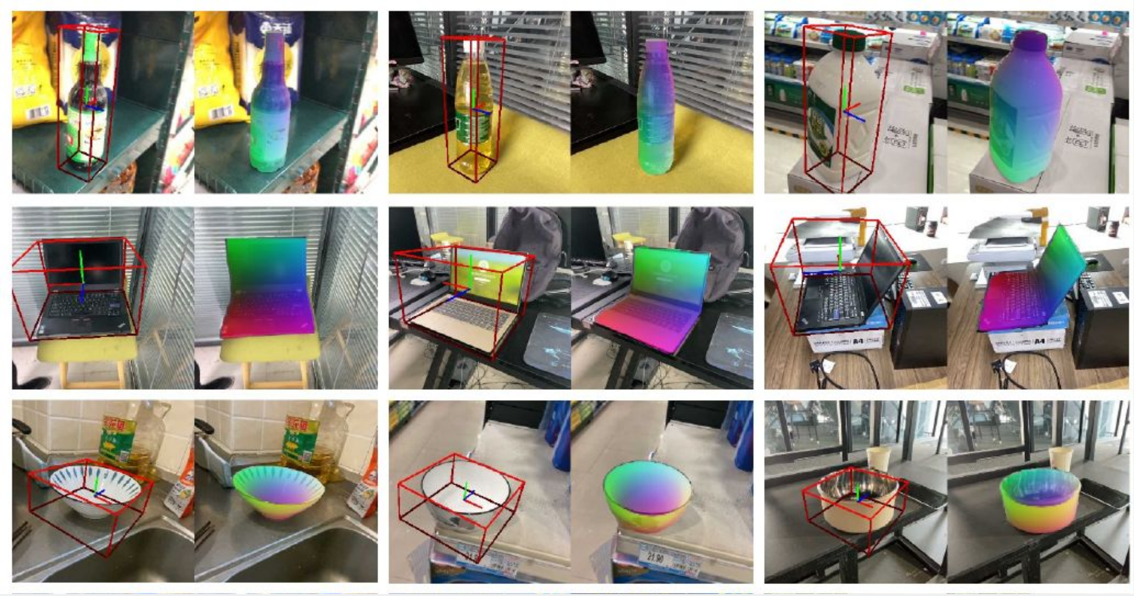
Background

1. Lack of Generalization



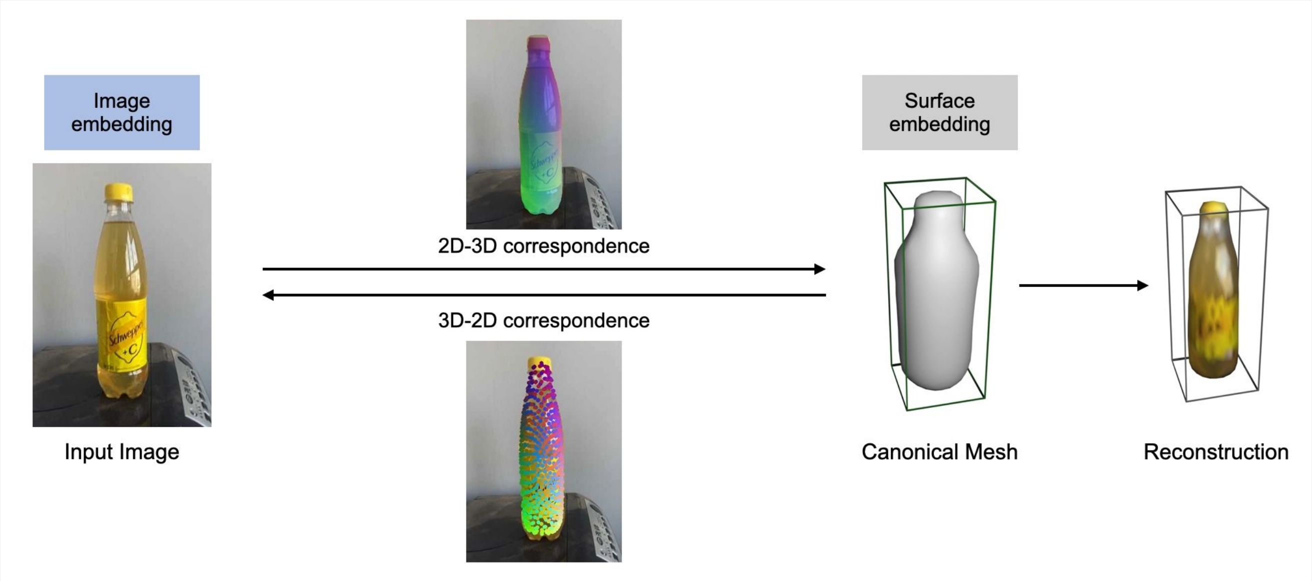
Background

2. Self-Supervised 6D Pose Estimation in the Wild



Background

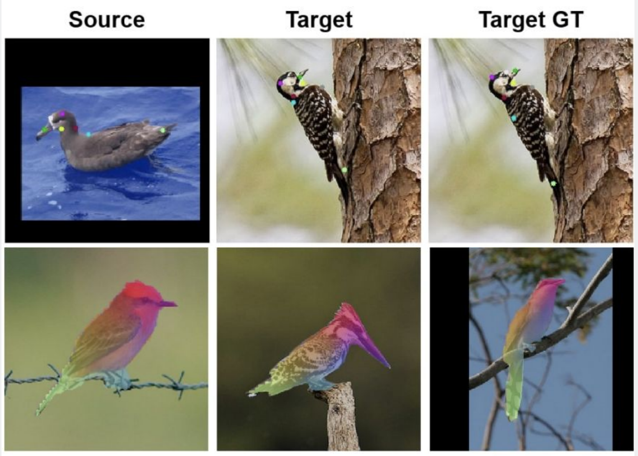
3. Categorical Surface Embedding



Related Works

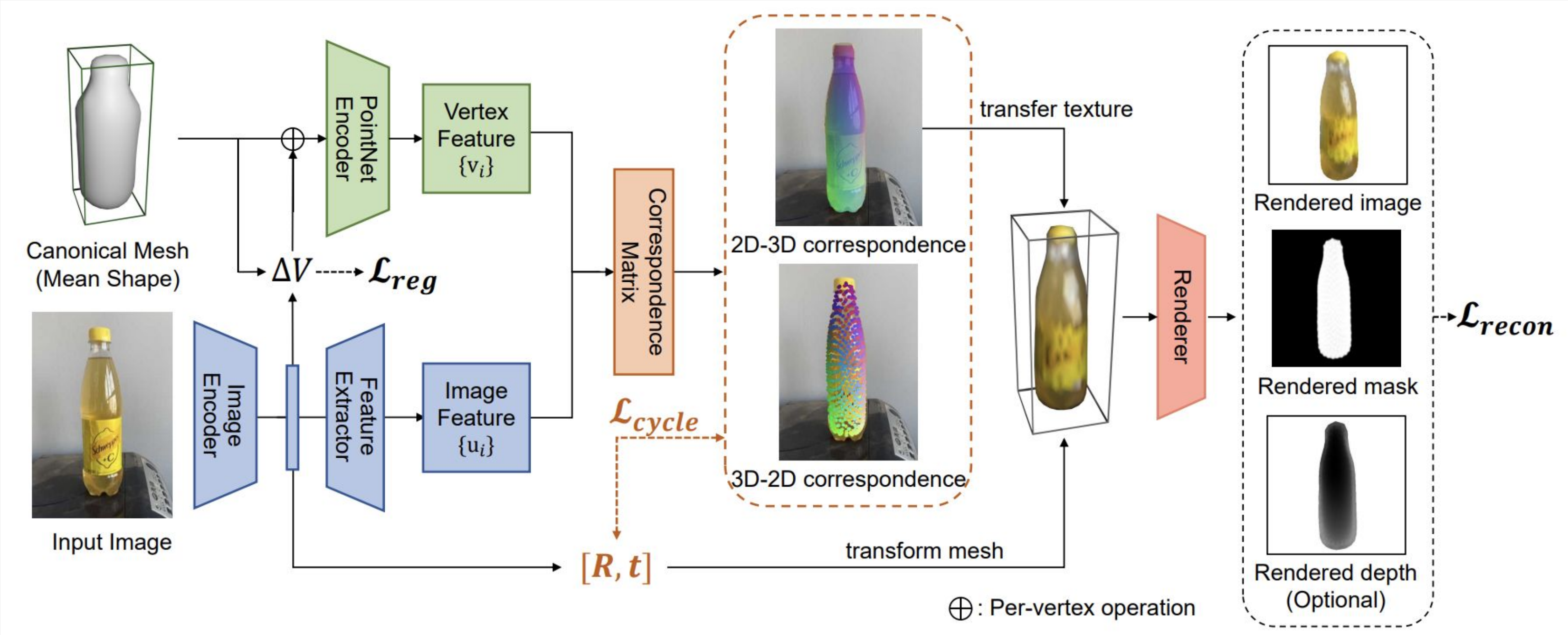
Semantic Encoding of Pixels from a DINO Trained Model

KeyPoint Transfer Task and Performance



Reproduction

Model Architecture



Pretrained Models

Model Accuracy					
Metric	Laptop	Camera	Bottle	Bowl	Mug
3D IOU: 25%	0.997	0.867	0.931	0.982	0.889
3D IOU: 50%	0.956	0.145	0.835	0.890	0.652
5°, 2cm	0.151	0.000	0.739	0.778	0.011
5°, 5cm	0.176	0.000	0.813	0.829	0.011
10°, 2cm	0.242	0.000	0.808	0.862	0.045
10°, 5cm	0.457	0.000	0.911	0.945	0.056

Retraining

Model Accuracy		
Metric	Pretrained Model	Our Training
3D IOU: 25%	0.997	0.999
3D IOU: 50%	0.956	0.864
5°, 2cm	0.151	0.024
5°, 5cm	0.176	0.028
10°, 2cm	0.242	0.083
10°, 5cm	0.457	0.167

Extension

Motivation

1. Limited hyperparameter tuning

Hyperparameters	Wild6D	REAL275	CUB
# of iterations	20,000	10,000	5,000
$(\beta_{\text{texture}}, \beta_{\text{mask}}, \beta_{\text{depth}})$ (Eq. 3)	$(0.05, 0.15, 0.1)$	$(0.05, 0.15, 0.1)$	$(0.05, 0.15, 0)$
$(\beta_{\text{2D-3D}}, \beta_{\text{2D-3D}}, \beta_{\text{inst}}, \beta_{\text{inst}})$ (Sec. 3.3)	$(0.02, 0.02, 0.05, 0.05)$	$(0.02, 0.02, 0.05, 0.05)$	$(0.01, 0.01, 0.1, 0.1)$
τ (Eq. 1)	0.1	0.1	0.1
k (Eq. 6)	200	200	200
$(\lambda_{\text{recon}}, \lambda_{\text{cycle}}, \lambda_{\text{reg}})$ (Sec. 3.3)	$(1, 1, 1)$	$(1, 1, 1)$	$(1, 1, 1)$

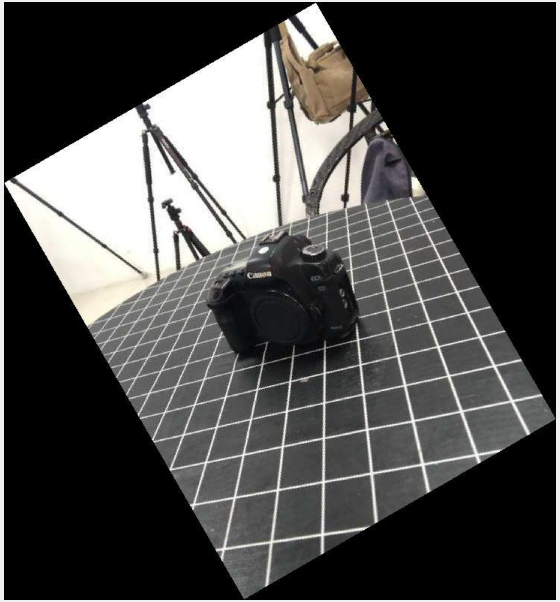
Hyperparameter Tuning

Model Accuracy			
Metric	weight-0.02	weight-0.05	weight-0.08
3D IOU: 25%	0.854	0.844	0.855
3D IOU: 50%	0.109	0.118	0.098

Motivation

2. Data Augmentation

rotate

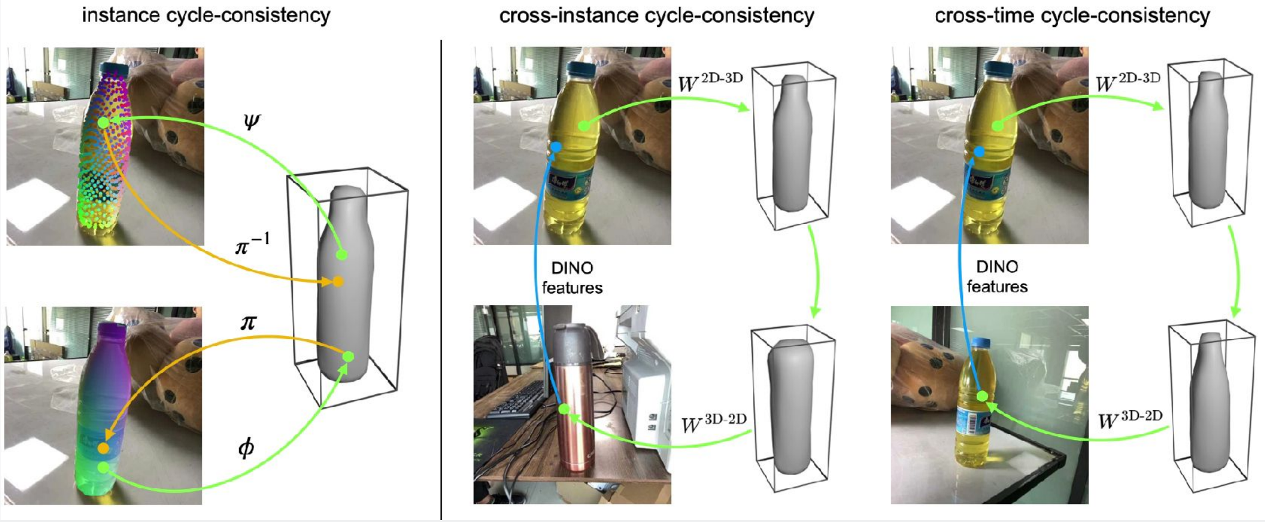


Data Augmentation

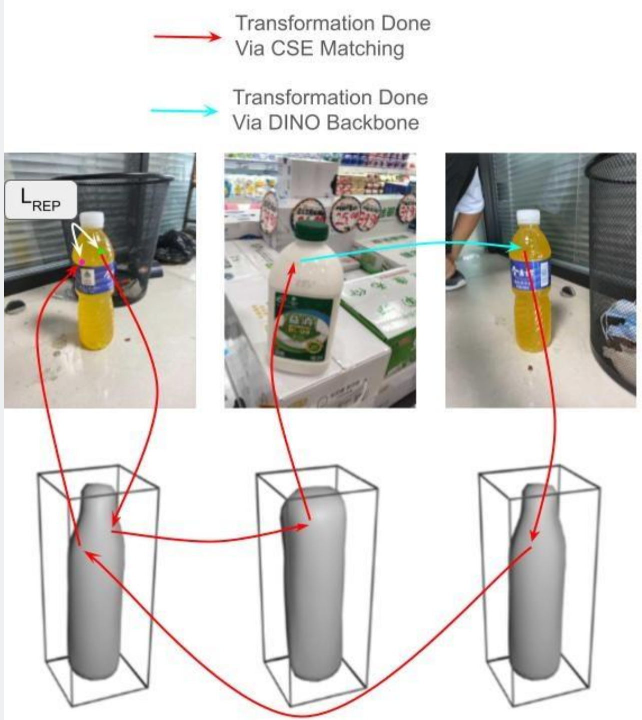
Model Accuracy				
Cycle-Loss-Weight	Metric	W/O augmentation	W/ augmentation	Improvement
0.02	3D IOU: 25%	0.854	0.864	0.170%
	3D IOU: 50%	0.109	0.097	-11.009%
0.05	3D IOU: 25%	0.844	0.851	0.829%
	3D IOU: 50%	0.118	0.101	-14.406%
0.08	3D IOU: 25%	0.855	0.857	0.233%
	3D IOU: 50%	0.098	0.091	-7.142%

Motivation

3. Cycle-consistency losses limitation
   (Don't account for intermediate mapping inaccuracies)



RepLoss Function



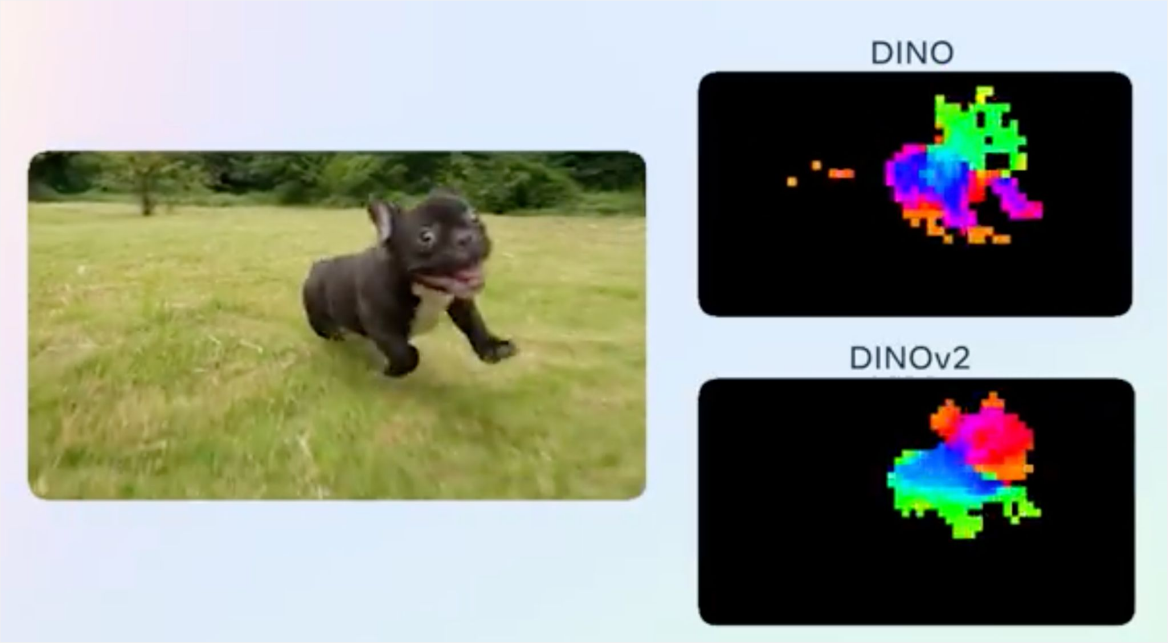
Model Accuracy			
Metric	W/O RepLoss	W/ RepLoss	Improvement
3D IOU: 25%	0.999	0.998	-0.090%
3D IOU: 50%	0.864	0.896	+3.702%
5°, 2cm	0.024	0.024	-0.752%
5°, 5cm	0.028	0.043	+55.844%
10°, 2cm	0.083	0.126	+52.042%
10°, 5cm	0.167	0.170	+1.927%

Motivation

4. Outperforms its own backbone

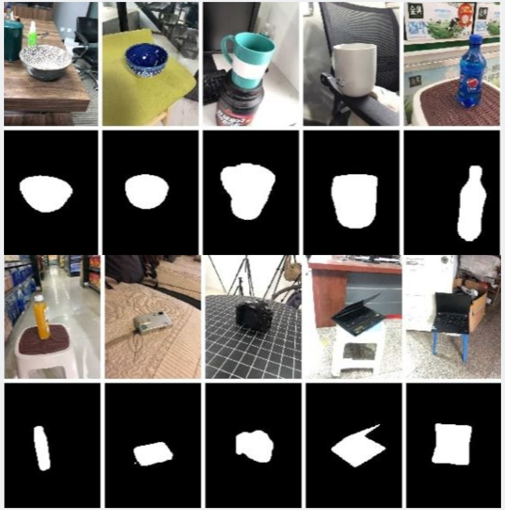
Method	3D/2D Transfer	PCK
VGG (Simonyan & Zisserman, 2014)	2D	17.2
DINO (Caron et al., 2021)	2D	60.2
Ours-2D	2D	**72.9**
Ours	3D	64.5

Replacing Backbone



Motivation

5. Ground truth requirements



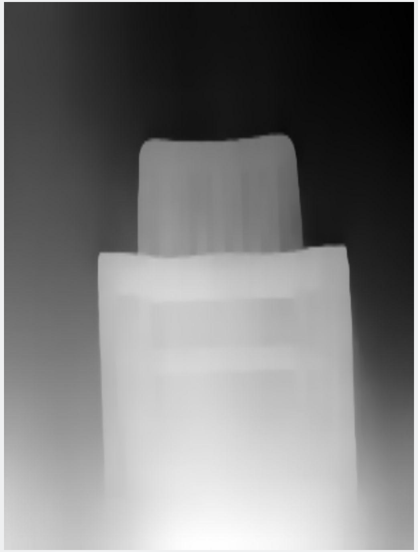
Segmentation Mask

Depth Map

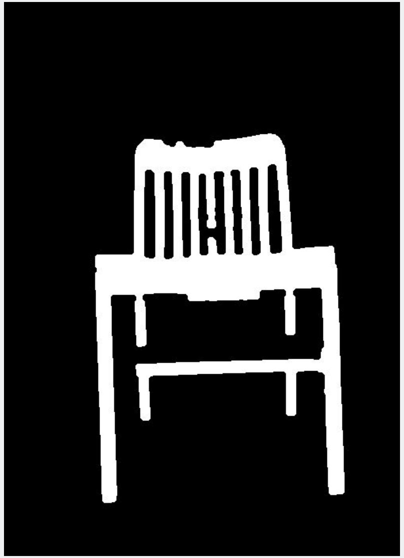
New Datasets

RGB-Image

Depth Map



Object Mask

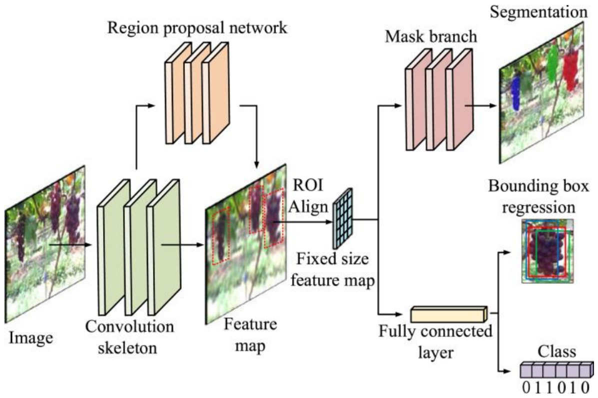


GrapeRob: A Grape Localization Pipeline for Automated Robotic Harvesting

Advaith Balaji
Isaac Madhavaram

Fruit Detection and Pose Estimation for Grape Cluster-Harvesting Robot Using Binocular Imagery Based on Deep Neural Networks

- Automation of Grape Harvesting
- Can be generalized for multiple fruits
- Lightweight, easily deployable model with high precision



Yin et al. 2021

The Bigger Picture...

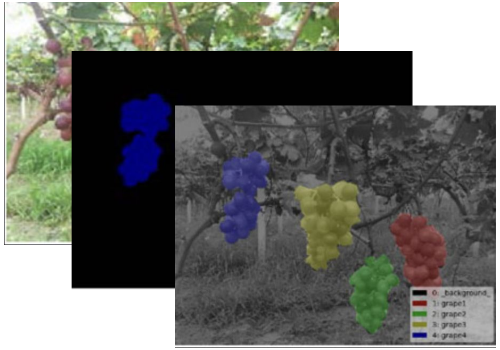
- Labor shortages and the inefficiencies of manual harvesting

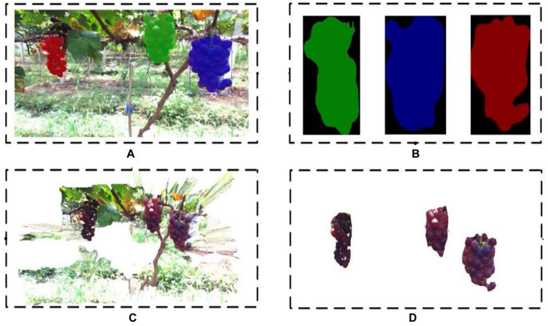
- Alleviate labor shortages and ensure sustainable grape production

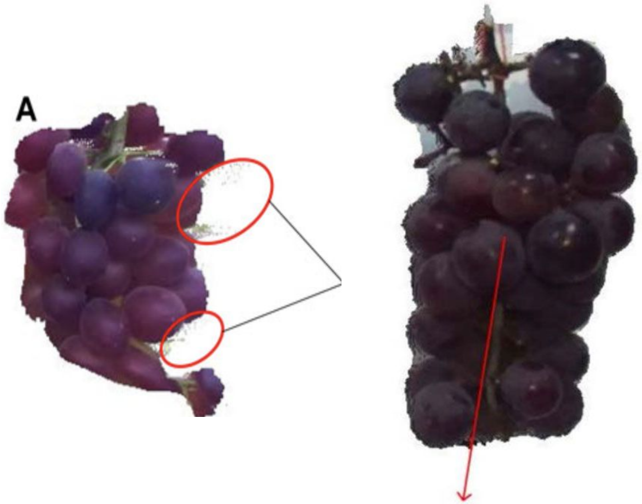
(72 million tons of grapes!!)

Approach

- Use binocular imagery to reconstruct a 3d point cloud of a segmented bunch of grapes

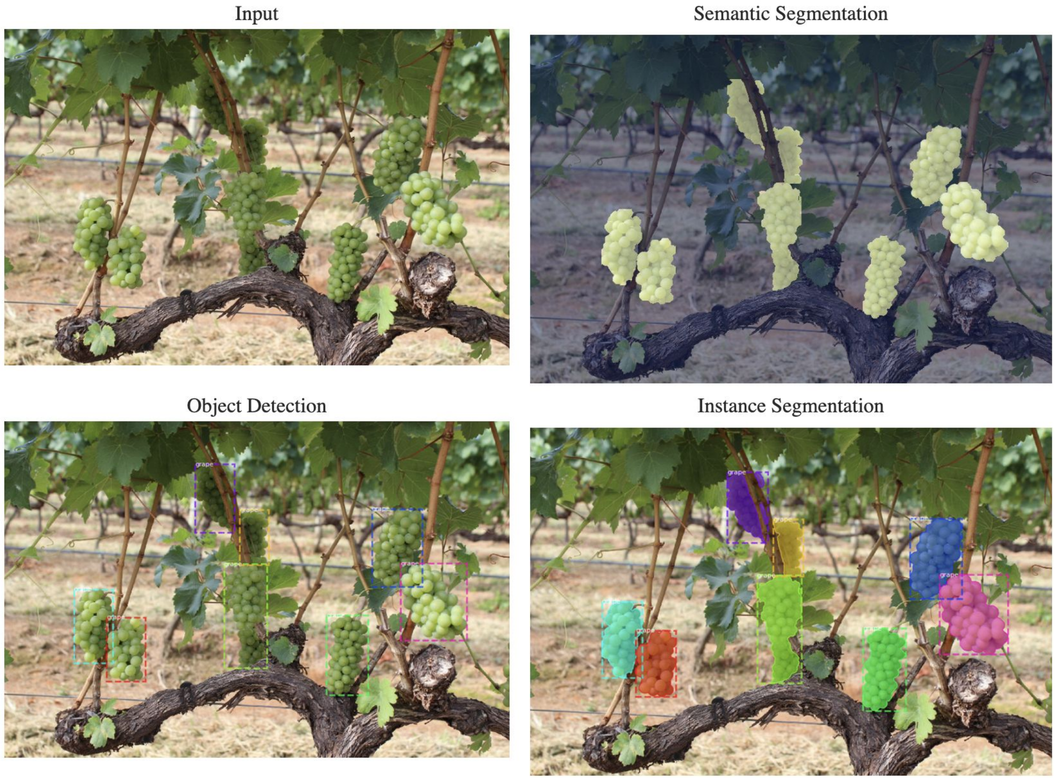






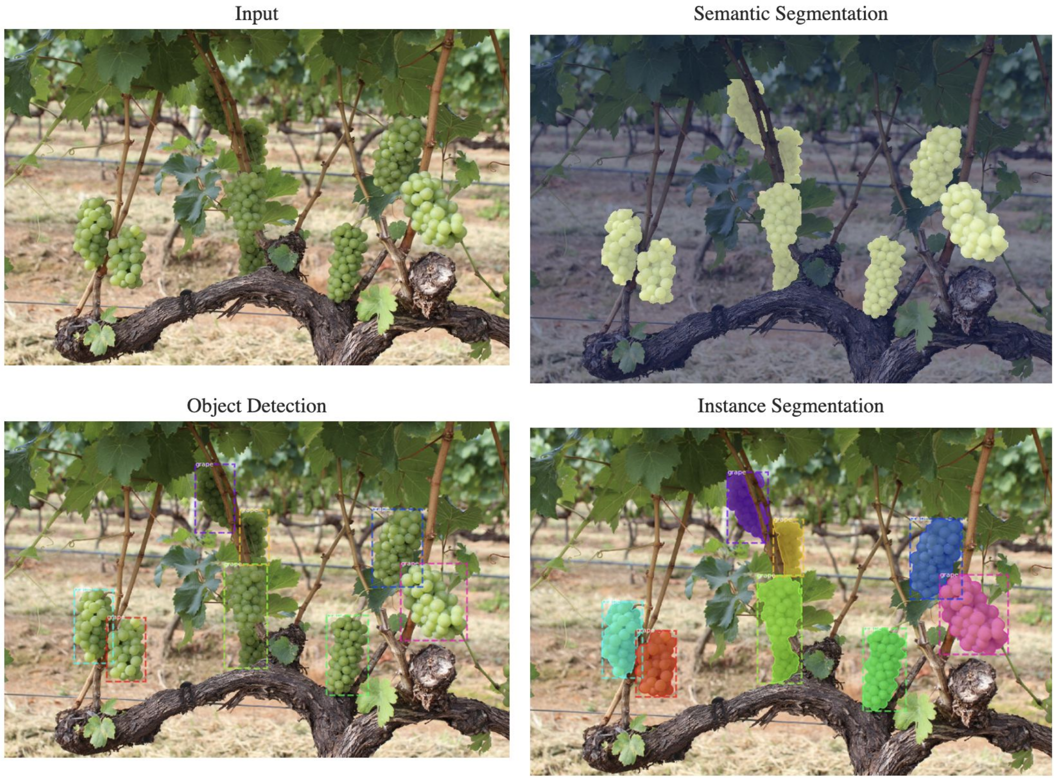
Yin et al. 2021

Data



Santos et al.

What is the clear problem with this??



Santos et al.

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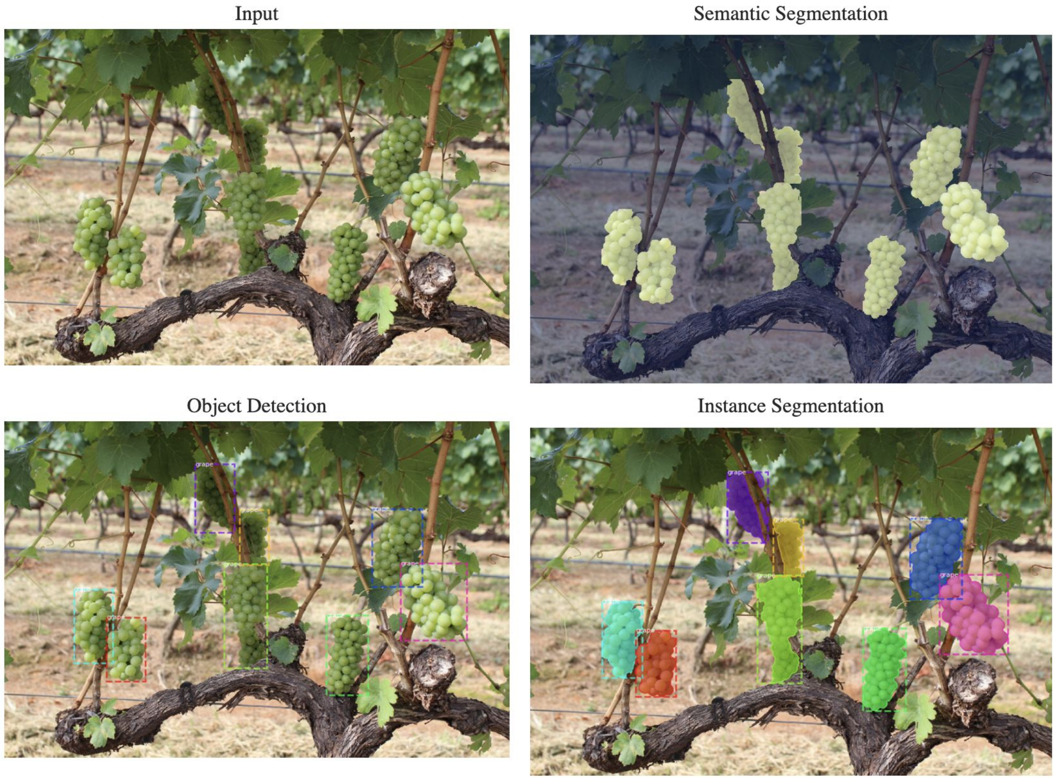

Must grasp at the stem!

Santos et al.

Results

Lighting conditions	Number of grapes	Precision/%	Recall/%	*IOU*/%
Frontlighting	72	92.31	97.30	83.23
Side-lighting	69	89.61	95.83	82.17
Back-lighting	65	86.67	92.86	80.61

Average detection time (s)	Average point cloud segmentation time (s)	Average total time (s)
1.1	0.6	1.7

Yin et al. 2021

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Yin et al. 2021

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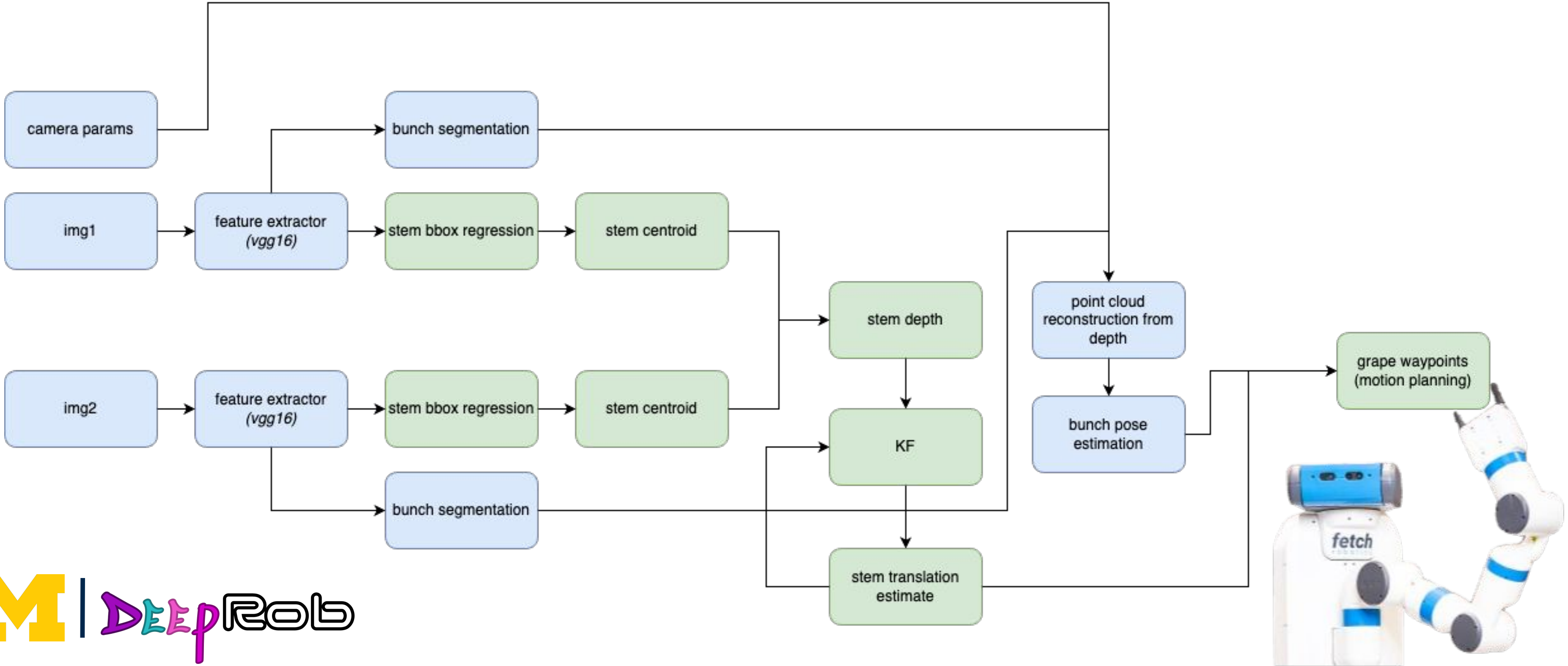
Average detection time (s)	Average point cloud segmentation time (s)	Average total time (s)
1.1	0.6	1.7

No robots!

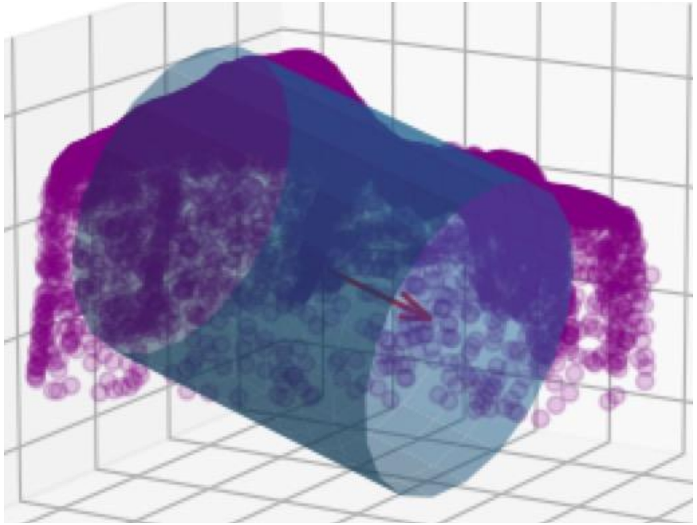
Yin et al. 2021

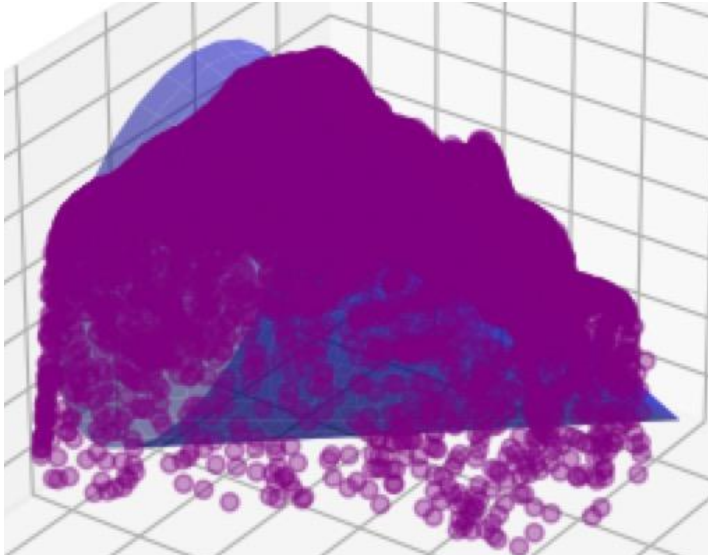
Our Proposal



Our Contributions

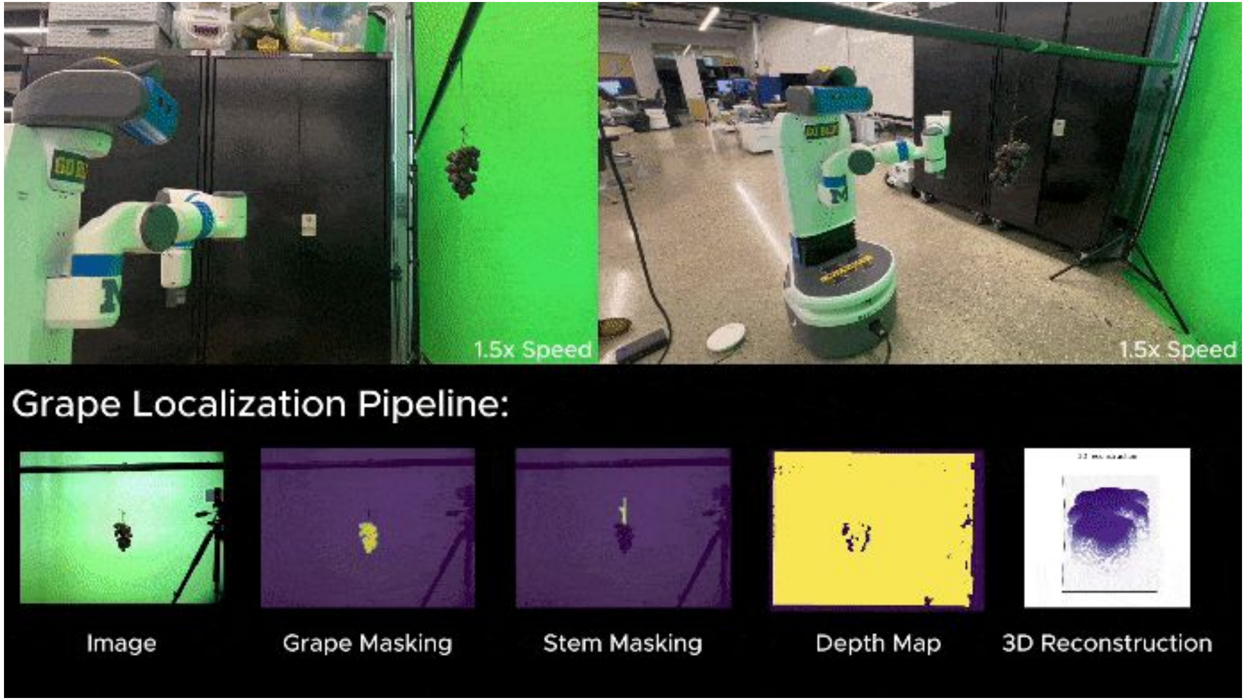
Our Contributions





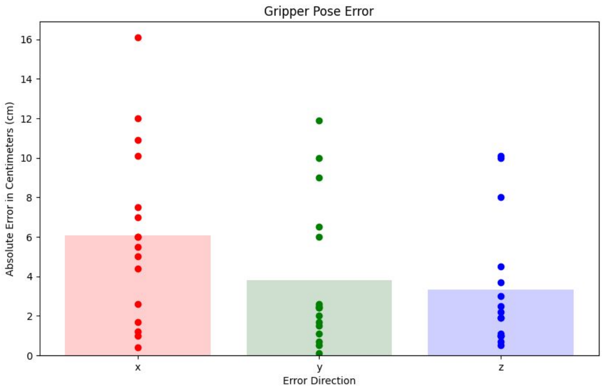
Our Contributions

Our Pipeline



Robot Experiments

- 86% Grasp Success Rate
- Average Pose Error:
  - 6.08 cm in x
  - 3.80 cm in y
  - 3.11 cm in z



Robot Experiments

- 86% Grasp Success Rate
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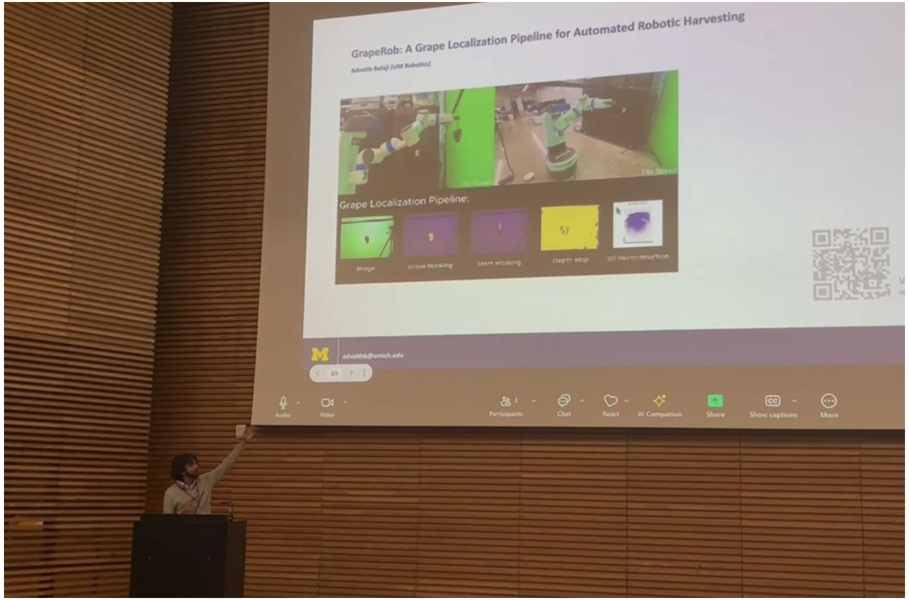


Presented at Michigan AI Symposium!

Aha Slides
(In-class participation)

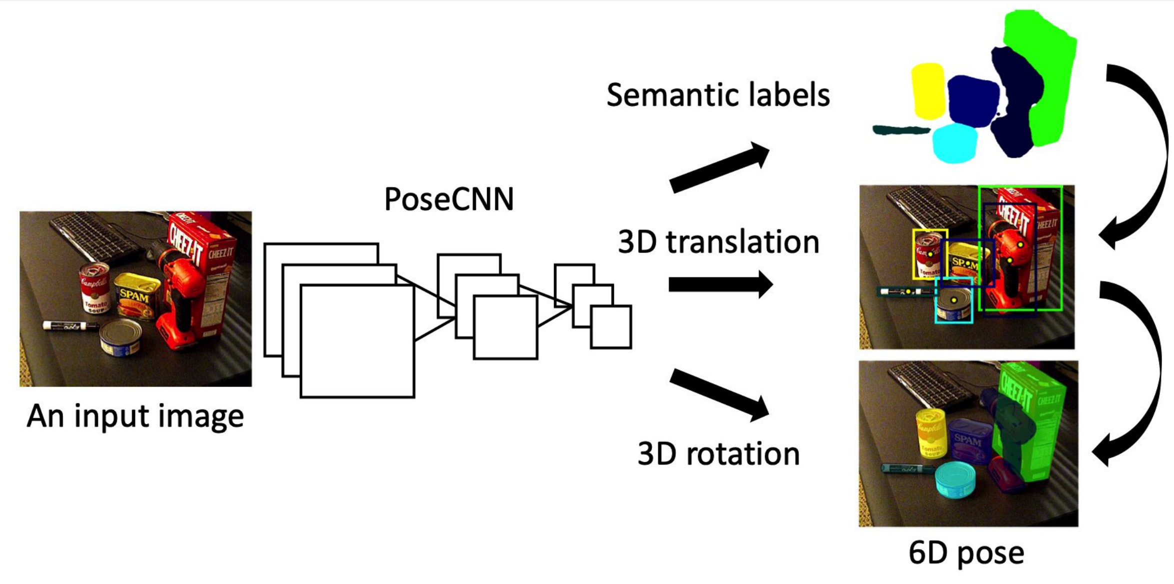
https://ahaslides.com/81CWI

(questions for our presenters?)

More on Robotic Grasping

Recap: Pose CNN

(Monday Feb.24 lecture - will be useful in P4)



Robotic Grasping

robotic manipulation

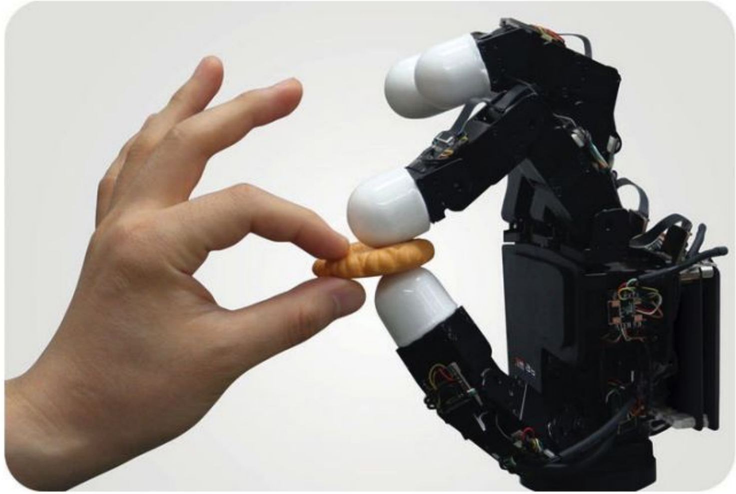


Figure 5.1: The Allegro Hand. Image retrieved from wiki.wonikrobotics.com.

Definition (Grasp):
A grasp is an act of restraining an object's motion through application of forces and torques at a set of contact points.

Robotic Grasping

robotic manipulation

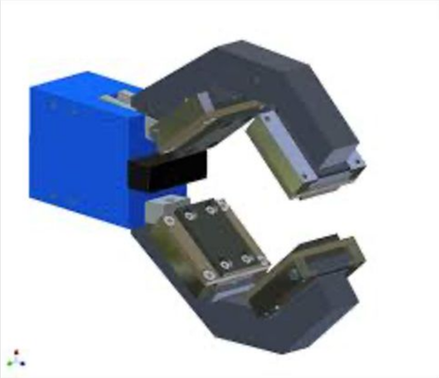
Challenges (Grasp):

- High-dimensional configuration of the gripper
- Choosing contact points can be difficult
- Ensure robot doesn't collide with environment
- Evaluate grasp quality (robust grasp, uncertainty)

Robotic Grasping - End Effectors

Parallel Gripper

https://onrobot.com/en/products/2fg7



Jaw Gripper

https://www.agi-automation.com/design-guidelines-for-pneumatic-gripper/

Dexterous Hand Gripper

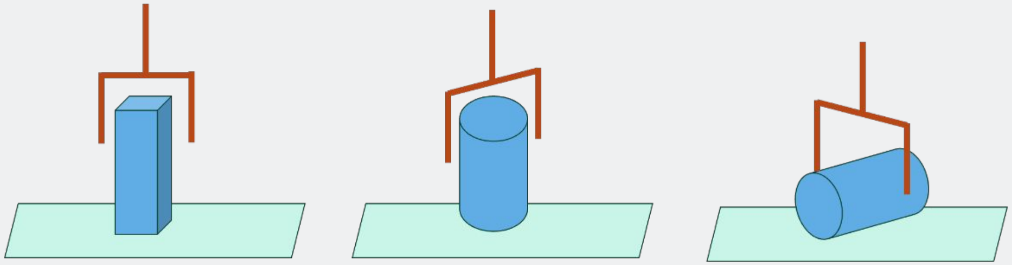
https://www.shadowrobot.com/

Suction Gripper

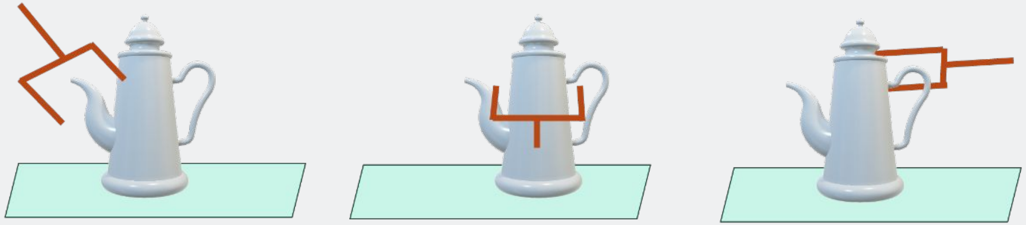
https://test.tm-robot.com/en/product/robotiq-vacuum-gripper-epick/

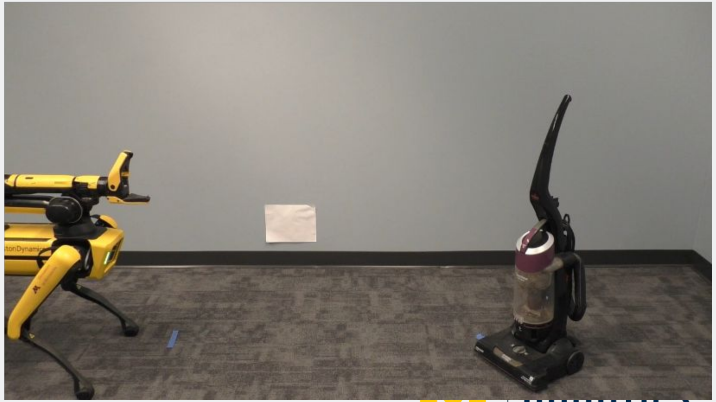
Robotic Grasping - Grasp Pose

- Grasping in SE(2) pose



- Grasping in SE(3) pose





Robotic Grasping - SE(2) Pose

Action Direction:

Top-down

Input:

RGB-D images, point cloud

Output:

$(x, \ y, \ \theta)$

- Location
- Rotation angle

M | ROBOTICS

Robotic Grasping - SE(3) Pose

Action Direction:

any 3D direction

Input:

volumetric representations (mesh, point cloud, TSDF, etc.)

Output:

(R , t)

- Rotation
- Translation

Robotic Grasping - SE(2) Pose

- Supersizing Self-supervision: Learning to Grasp from 50K Tries and 700 Robot Hours https://arxiv.org/pdf/1509.06825v1
- Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics https://arxiv.org/abs/1703.09312
- Sample Efficient Grasp Learning Using Equivariant Models https://arxiv.org/pdf/2202.09468
- Grasping with kirigami shells https://www.science.org/doi/10.1126/scirobotics.abd6426

Robotic Grasping - SE(3) Pose

- High precision grasp pose detection in dense clutter
  https://arxiv.org/pdf/1603.01564
- GraspNet-1Billion (large-scale benchmark)
  https://openaccess.thecvf.com/content_CVPR_2020/papers/Fang_GraspNet-1Billion_A_Large-Scale_Benchmark_for_General_Object_Grasping_CVPR_2020_paper.pdf
- Contact-GraspNet (Cluttered scene)
  https://arxiv.org/pdf/2103.14127
  https://github.com/NVlabs/contact_graspnet
- GraspNeRF (Multiview, Transparent and Specular Objects)
  https://pku-epic.github.io/GraspNeRF/