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### Experimental Validation of Uncertainty Quantification Methods for Robot Perception

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At the total Perception

\n
$$
\mathscr{C}\left(X_{test}\right) = \left\{ y : \hat{f}\left(X_{test}\right)_y \ge 1 - \hat{q} \right\}
$$
\nOur results demonstrate that the formula for the following equations are given by:

\n
$$
\mathscr{C}\left(X_{test}\right) = \left\{ y : \hat{f}\left(X_{test}\right)_y \ge 1 - \hat{q} \right\}
$$

**Object Detection**

Detection Results

Conformal **Prediction** d<br>nformal<br>ediction

Visual Perception

Trustworthy Results

<u> A B B B B B B B B B B B B A B B B</u> **Safe** Navigation **Decisions** 

# 2. Object Detection (cont.) **RESULTS**

# Experimental Validation of Uncertainty Quantification Methods for Robot Perception Yifei (Bruce) Li, Department of Electrical & Systems Engineering

**Environment** 

Research Advisor: Professor Yiannis Kantaros

# **Background**

In real-world settings, from woking in manufacturing plants to self driving on highway, robots empowered by Machine Learning (ML) models are tasked with complex, dynamic tasks that demand high levels of precision and adaptability. The reliability of these systems hinges on the perception capabilities of ML model, making uncertainty quantification methods vital. Conformal prediction is a user-friendly paradigm for creating statistically rigorous uncertainty sets/intervals for the predictions of such models. [1] It ensures that robots can effectively assess and respond to varying conditions with safe and trustworthy actions, reducing the risk of errors and enhancing overall system performance. *rital. Conformal prediction is a of the prediction is a of*  $\blacksquare$  *<b>Presulting in multiple bounding boxes with each labeled with and the prediction is a Figure 1: Prediction set Musumersection over union (fou) is greater than 0.3.* uch models. [1] It ensures that<br>I cond to verying conditions with  $\frac{1}{2}$  (a.k. a.k.a. conformal interesting to generate prediction  $\frac{1}{2}$  for each bhore in detections do  $f(x) = \frac{1}{3}$ . Compute intersection over union

### PROBLEM STATEMENT  $\sum_{i=1}^{\infty}$  *\*  $\sum_{i=1}^{\infty$

The purpose of this research project is to experimentally validate the  $z_1$  and  $z_2$  and  $z_1$ effectiveness conformal prediction in object detection of a control algorithm on a ground robot platform.

During our test in Gazebo simulator, With lack of custom trained detection model, the algorithm performs sub-optimally in simulated world. Which highlights the fact that conformal prediction can provide statistically promising results when model predictions are inaccurate.  $\Gamma$  a.k.a. conformal inference) is a straightformal inference  $\Gamma$  straightformal inference) is a straightforward way to generate prediction sets way to generate prediction sets way to generate prediction sets was the  $\$ for any model  $\alpha$  is we will introduce it with a short-duce interval  $\alpha$  short, produce  $\alpha$ 

> [1] A. N. Angelopoulos and S. Bates, A Gentle Introduction to Conformal Prediction and Distribution-Free Uncertainty Quantification. 2022. [2] S. Li, S. Park, X. Ji, I. Lee, and O. Bastani, Towards PAC Multi-Object Detection and Tracking. 2022. [3] L. Andéol, T. Fel, F. D. Grancey, and L. Mossina, Confident Object Detection via Conformal Prediction and Conformal Risk Control: an Application to Railway Signaling. 2023. [4]C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors," 2023. conformal prediction [1] **Find** Prediction and Conformal Risl comomarpleuction.com/up/A.iv.Angelopoulor/<br>Public formulations example in the core of the core of the calculate core in the calculate of the calculabels of the calculabels of the calculabels of the calculabels of the calculate of the calculate of the calculate of the calculate of the



# INTRODUCTION

## **Given**

- The physical environment distributed with objects.
- A robot and its planned navigation control scheme.

# **Find**

• Make safe, trustworthy actions based on result of object detection and conformal prediction.

> In this research project, we presented an experimental validation of this property *marginal coversing quantification for robot perception*.

# **Purpose**

Our results demonstrated that the proposed approach was effective in exty [1] and the calibration of the calibration of the calibration in the true label with high step that contain the true label with high

By validating the effectiveness of the conformal prediction in a simulated setting with the specific model of robot, we can contribute to the development of more safe and trustworthy robotic controls. *f*(*Xi*)*<sup>Y</sup><sup>i</sup>* to be  $n+1$  one is the softmax of the softmax o

• Assume two bounding boxes are over the same object if their

r union

- Common object detector assumes each bounding box contains one instance of object class.
- intersection over union (IoU) is greater than 0.3.
- multiple class instances and scores.

- For the robot perception algorithm, we choose YOLOv7 object detection with pre-trained weights on the Microsoft COCO (Common Objects in Context) Dataset. [4] S<br>Ite
- State-of-the-art performance in realtime object detection, capable of identify and classify multiple objects in complex environments with minimal latency and high precision.







# **1. Setup**

# FUTURE DIRECTIONS

# REFERENCES

- end for  $r=11$  and for i.i.d. pairs of images and contract unseen during training,  $r=11$  and contract unseen during training,  $r=11$  and  $r=$ 
	- 12: end for

### **3. Conformal Prediction 12. Conformal Prediction**

Given each output (bounding box) of object detection that **Formally, Suppose we have included as input and they experience we have included and they experience of the support of**  $\mathcal{A}$  **and they experience of**  $\mathcal{A}$  **and they experience of**  $\mathcal{A}$  **and they experience of \mathcal{A**  $\overline{\phantom{a}}$ *Given each output (bounding box) of object detection that* 

Find conformal score  $(1 -$  score of true class): ̂  $\hat{f}(x) \in [0,1]^K$  $s_i = 1 - \hat{f}$ *f*  $s_i = 1 - \hat{f}(X_i)_{Y_i}$  $I^{(1)}$   $I^{(2)}$   $I^{(3)}$   $I^{(3)}$   $I^{(4)}$ tind conformal score (1  $-$  score of true class):  $\frac{1}{2}$   $\frac{1}{2}$  reserve a moderate number (e.g., 500) of fresh i.i.d. pairs of images and classes unseen during training, (*X*1*, Y*1)*,...,*(*Xn, Yn*), for use as calibration data. Using  $p_i = 1 - f(X_i)$ , K<sub>i</sub>, K<sub>i</sub>

# **EDURE** Construct empirical quantile  $\hat{q} = \frac{|\langle n+1 \rangle \langle 1 - \alpha \rangle|}{|\langle n+1 \rangle \langle 1 - \alpha \rangle|}$ -th

**Environment**  $\vdots$  element of  $s_1, ..., s_n$  from calibration set e Pi a **Exercise Figure 1.1** Make the inference to choose form set of classes: In this research project, we pre  $\sum_{i=1}^{\infty}$  introducing some terms that will be set the *conformal squares quartition*  $q$ e PI, d<br>at *s*<sup>1</sup>, *s*<sup>n</sup>, where depending function (s<sup>1</sup>, q<sup>1</sup> q<sup>2</sup>/  $\frac{2}{\pi}$  d<sup>2</sup>  $\frac{1}{\pi}$  q<sup>1</sup>

 $y$ *min*,  $bbox_2 \rightarrow y$ *min*)  $y \rightarrow y \rightarrow y \rightarrow y \rightarrow y$  $\overline{a}$ *<sup>f</sup>*(*x*) <sup>2</sup> [0*,* 1]*<sup>K</sup>*. Then, we

(1) compute scores on holdout data (2) get quantile (3) construct prediction set *# 1: get conformal scores. n = calib\_Y.shape[0]* ed conformatiscores.  $n = \text{cutoff}$  .shaperof sand  $\text{cutoff}$  is the conformation ( $\text{call}$  sale  $\text{call}$ ).softmax(dim=1).numpy() cal\_scores = 1-cal\_smx[np.arange(n),cal\_labels] **Future directions could be: imp** *# 2: get adjusted quantile*<br>
a level = **pp** seil((p+1) \* (1 $q$ \_level = np.ceil $((n+1)*(1-a1pha))/n$ qhat = np.quantile(cal\_scores, q\_level, method='higher') is low, i.e., when the spectrum of more call in the model is badly wrong. Next conformal, scores,  $n = calib$   $Y, shape[0]$  and  $A$ *f*(*X*test)*<sup>y</sup>* 1 *q*  $\frac{q_{\text{max}}}{q_{\text{max}}}\left(\frac{q_{\text{max}}}{q_{\text{max}}}\right)$  integrate with  $\epsilon$ 

Future directions could be: implement classification with Adaptive **Prediction Sets**[1]; train custom detection models; test the perception and all classes Prediction Sets[1]; train custom detection models; test the perception  $\frac{q_{\texttt{level}} = np\cdot \text{cell}((n+1)*(1-a1pna))/n}{n}$  method and analyze it's performance in physical lab setting; and integrate with existing navigation algorithms.

# **2. Object Detection**

### METHOD & PROCEDURE To construct *C* from

• We will use the Turtlebot 3 Waffle Pi, a 2-wheel ROS based ground robot platform with build in camera, in the Gazebo simulated world. prediction set *C*(*X*test) = *{y* :

$$
\hat{q} = \frac{\lceil (n+1)(1-\alpha) \rceil}{n} - \text{th}
$$

That is granted to satisfy [1]: *f*(*X*test)*<sup>y</sup>* 1 *q*  $\begin{array}{ccc} \cdot & \cdot & \cdot & \cdot & \cdot \end{array}$ example 2). Remarkably, this algorithm gives prediction sets that are guaranteed to satisfy (1), no matter pre<br>In the guaranteed to satisfy (1), no matter prediction sets that are guaranteed to satisfy (1), no matter of t **nat is granted to sate** ˆ

 $1 - \alpha \leq \mathbb{P}\left(Y_{test} \in \mathcal{C}\left(X_{test}\right)\right) \leq 1 - \alpha +$ 

Object	probability. [2]	
Detection	$1 - \alpha \leq \mathbb{P}\left(Y_{test} \in \mathcal{C}(X_{test})\right) \leq 1 - \alpha + \frac{1}{n+1}$	By validating the effectiveness

prediction set  $\frac{3}{5}$   $\frac{4}{5}$   $\frac{5}{1}$   $\frac{5}{5}$   $\frac{1}{1}$   $\frac{1}{2}$  Fig. 2 illustration of [3] L. Archives [1]  $\frac{2}{5}$  Predi Fig. 3 conformal prediction Python code [1]

![](_page_1_Picture_69.jpeg)

6:  $x\_max \leftarrow min(bbox_1 \rightarrow x\_max, bbox_2 \rightarrow x\_max)$  Fig. 4,5,6 bounding boxes, labels of detected objects with conformal prediction in random selected COCO dataset images  $F_1$ . Prediction  $x_1 \rightarrow x$  min  $bbox_2 \rightarrow x$  min) backpack, handbag, clocks} {person, car, bus, truck, stop sign, {cat, cup, toilet, sink, book} {person, bottle, knife, sandwich, pizza, donut, cake, chair, couch, dining table}

![](_page_1_Picture_73.jpeg)

*f* and the calibration data, we seek to construct a

![](_page_1_Picture_1852.jpeg)

prediction\_sets = val\_smx >= (1-qhat) *# 3: form prediction sets*

![](_page_1_Figure_52.jpeg)

class

![](_page_1_Picture_72.jpeg)

# We first tested the object detection with conformal prediction with still images random selected COCO dataset: