

vision2tactile: Feeling Touch by Sight



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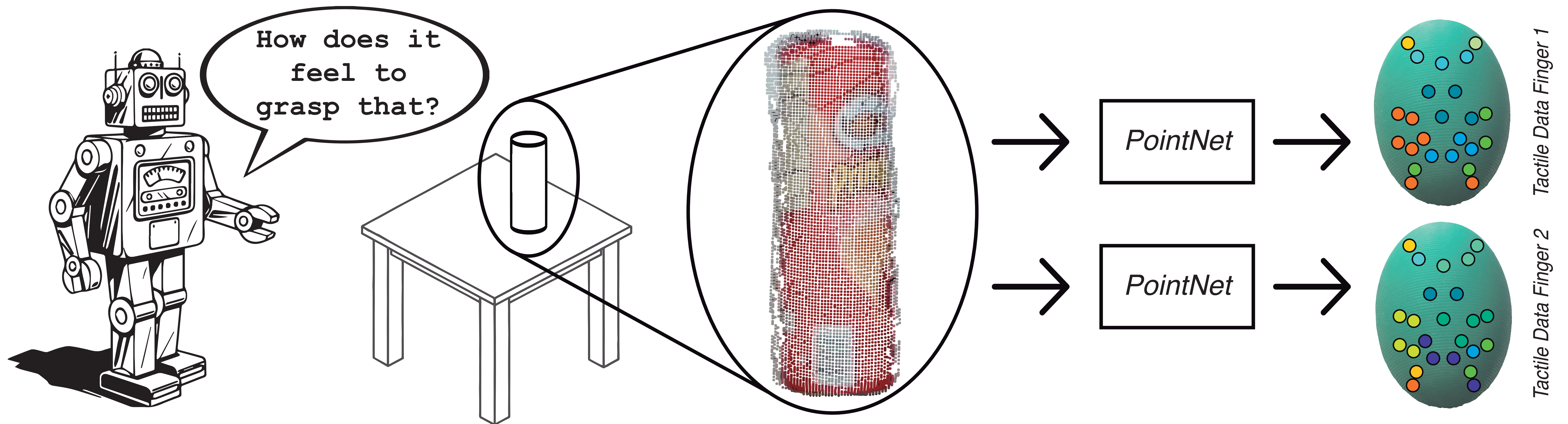
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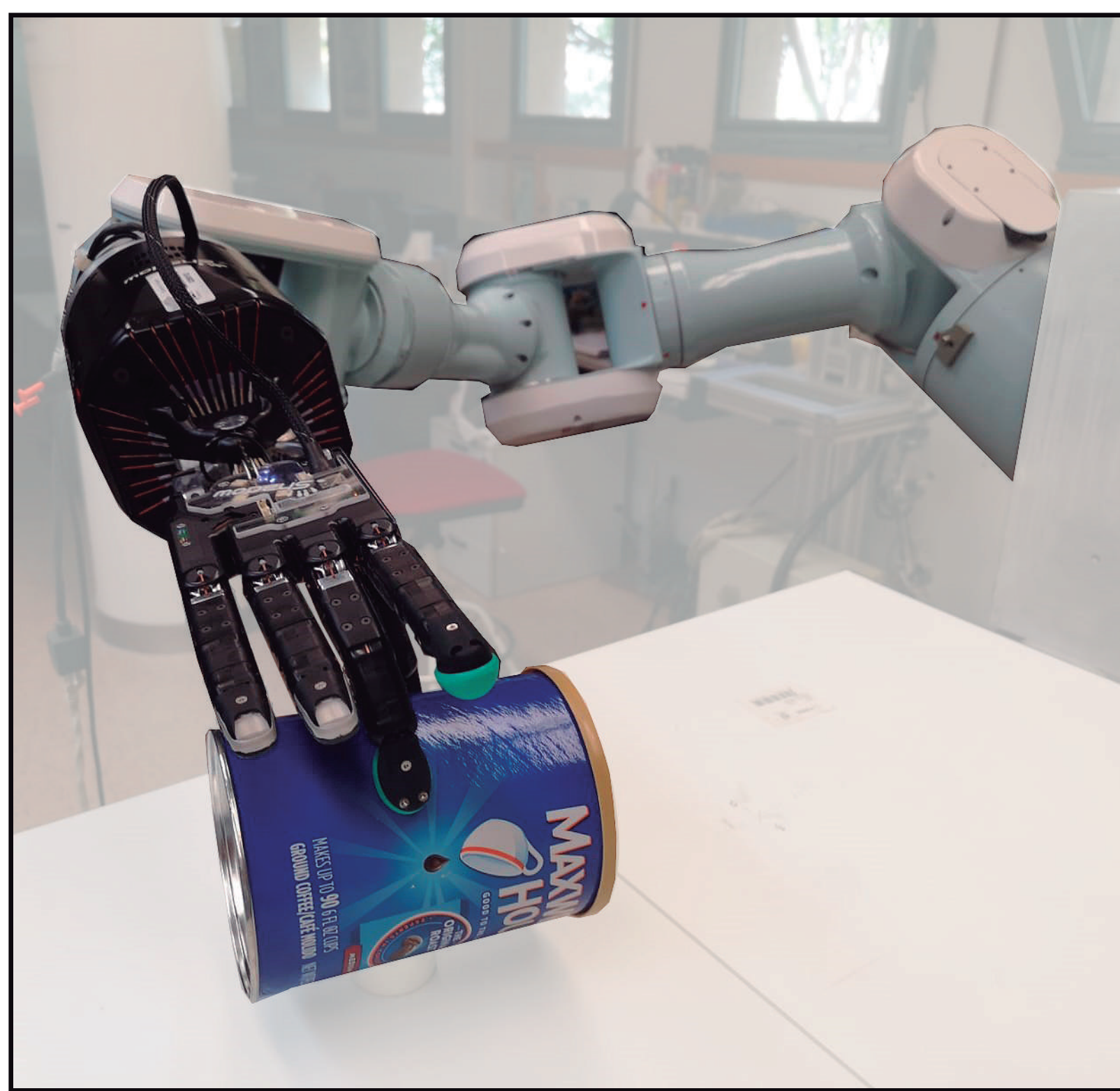
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Problem Statement & Approach



Methodology

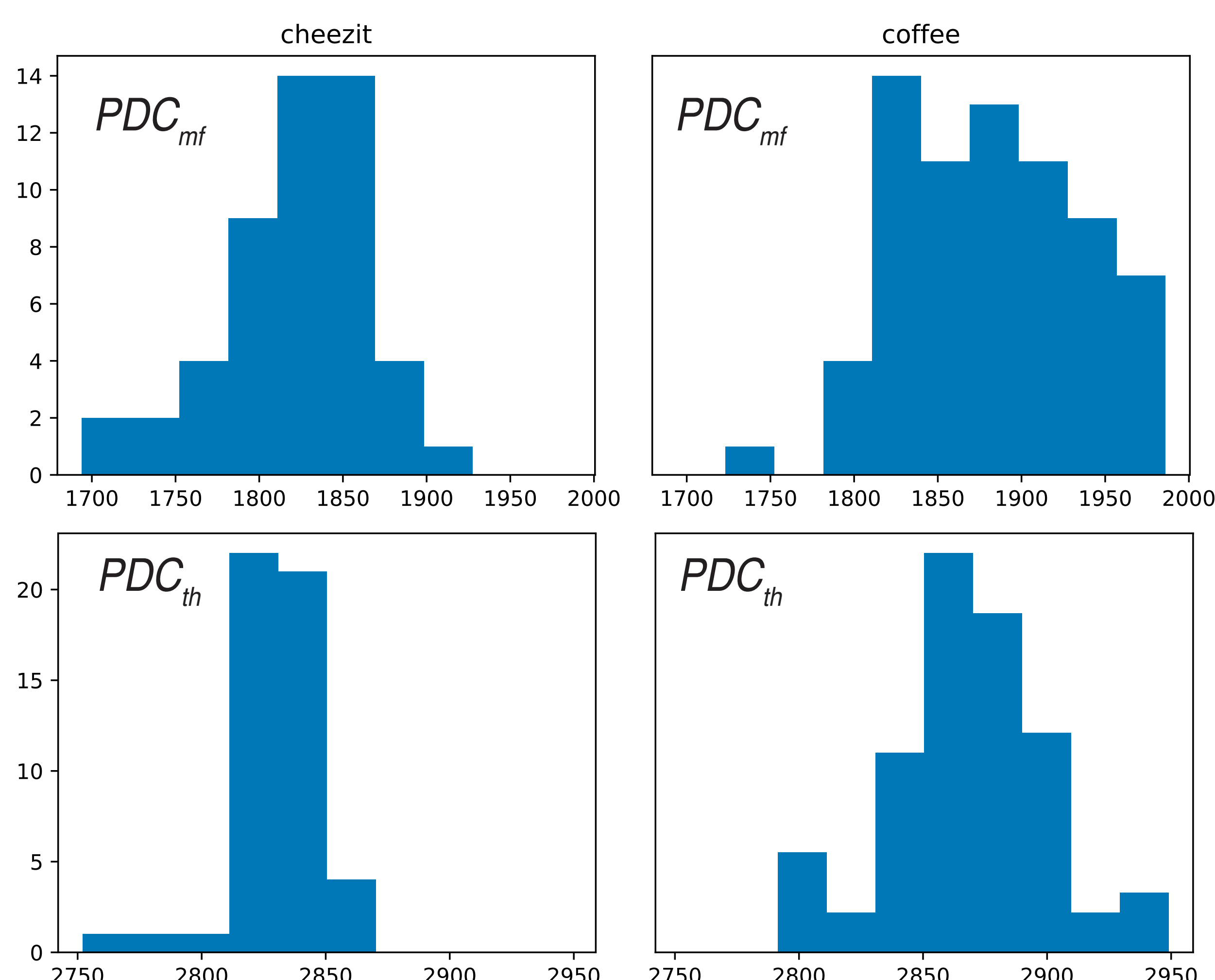


Our solution for **learning to regress tactile responses from visual perception** is composed of the following:

- **Robotic System:** Shadow dexterous hand equipped with BioTac SP sensors and mounted on a Mitsubishi PA10. Vision is acquired from a Intel RealSense D415 depth camera. We only use middle finger and thumb for grasps.
- **Visual Representation:** We use 3D point clouds as a visual stimulus for this learning task. Objects are segmented from the background and only position information is used. That is, points only hold 3D coordinates.
- **Tactile Responses:** Two task are identified. *Task A* aims to learn to regress global pressure value PDC for each of the two sensors. In contrast, *Task B* aims to learn to regress the 24 electrodes values for each of them.
- **Network Architecture:** Modified PointNet network for regression. Point clouds are downsampled to 500 points and normalised to the unit sphere with centre at the cloud's centroid. Tactile data are scaled to range $[0, 1]$.
- **Data Collection:** We collected data from real grasps on 4 objects from the YCB object set (Pringles can, Coffee can, Sugar box, CheezIt box). 50 grasps were carried out on each of them using GeoGrasp as our method for finding stable grasps. Find more at: <https://github.com/yayaneath/vision2tactile>

Experimentation

Due to construction reasons, the **sensors behave differently under the same conditions**. As a result, the range of values of the two sensors used are different: the sensor on the middle finger does not exceed values above 2000 while the thumb's sensor is always above that. Hence, **we trained one network for each sensor**, though sharing architecture and hyper-parameters. Networks were trained optimising the Root Mean Squared Error ($RMSE$) and 5-fold cross-validation was carried out.



Distribution of PDC values for middle finger's sensor (PDC_{mf}) and thumb's sensor (PDC_{th}) after grasping two different objects.

REGRESSING PDC VALUES

Training on the cylinder-like objects yielded an average $RMSE$ of 0.076 and 0.067 for PDC_{mf} and PDC_{th} respectively. Scaling those errors back to the sensors' PDC range, they equal 153 and 208 units. Similarly, training on box-like objects, the errors are 0.081 (164 units) and 0.089 (278 units) for each sensor. This shows that **it is possible to learn to regress PDC using PointNet**. However, the error is still as large as the range of values for each of the sensors. Finally, training with one type of object and testing on the other kept the mean error at 165 (train on cylinders and test on boxes) and 236 (train on boxes and test on cylinders) units.

REGRESSING ELECTRODES VALUES

Training on cylinder-like objects yielded an average $RMSE$ of 0.060 and 0.061 for middle and thumb sensors. Scaled back to the sensors' electrodes range, those are 231 and 216 units. Training on box-like objects, we obtained errors equal to 0.055 (212 units) and 0.066 (232 units). As expected, the **errors are higher since the network had to learn to regress more values**. Training with one type of object and testing on the other rose the errors to 310 and 317 points for each sensor.

Open Opportunities

- Generate realistic tactile data in simulation... real2sim!
- Provide simulated agents with rich tactile information
- Ease sim2real transfer using a tactile model learnt in reality
- This work points towards a new direction with lots of open questions!