Bayesian Viewpoint-Dependent Robust Classification Under Model and Localization Uncertainty

[1]Technion - Israel Institute of Technology, Israel

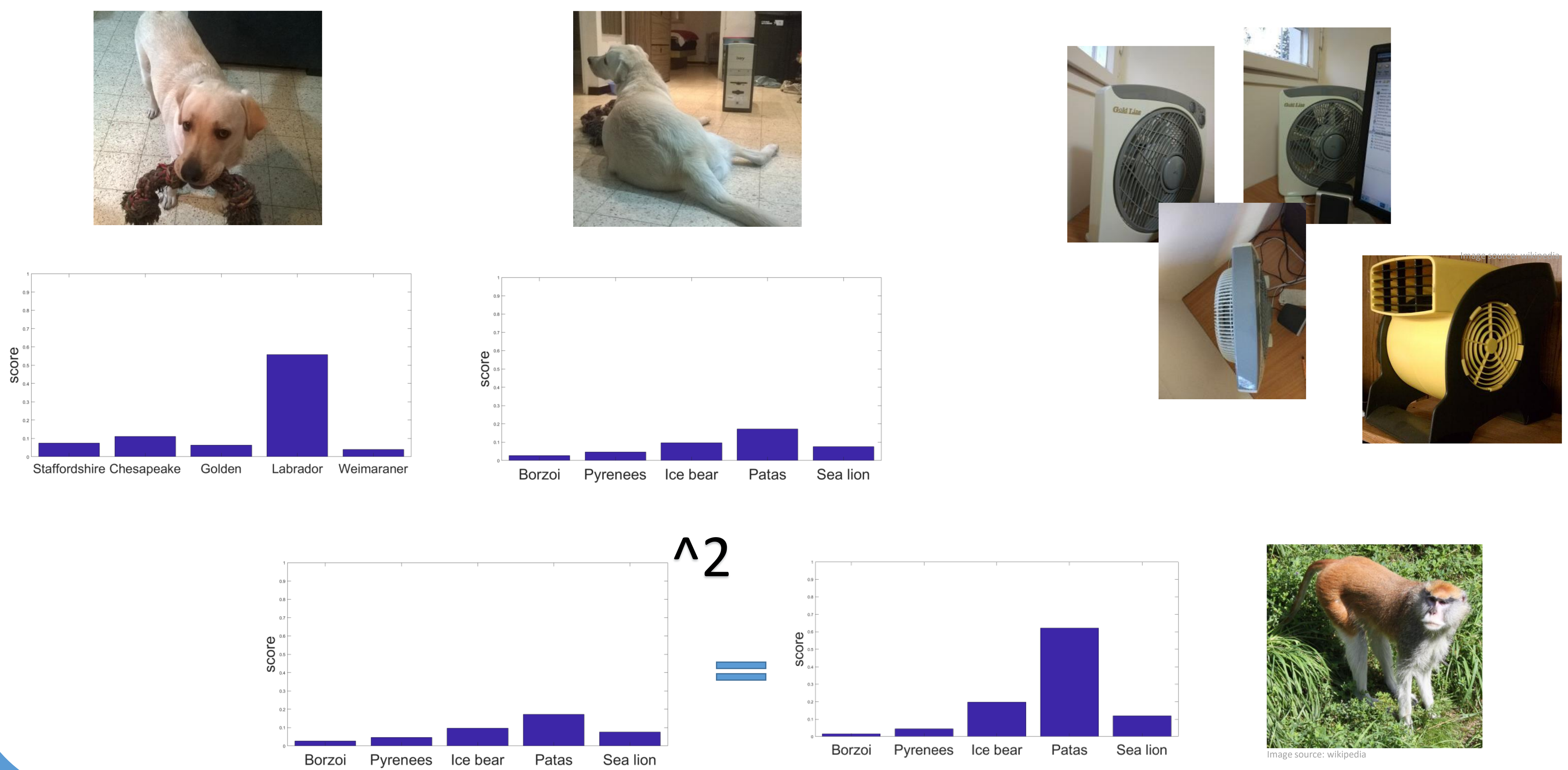
Yuri Feldman[1] and Vadim Indelman[1]

ANPL Autonomous Navigation and Perception Lab

TECHNION Israel Institute of Technology

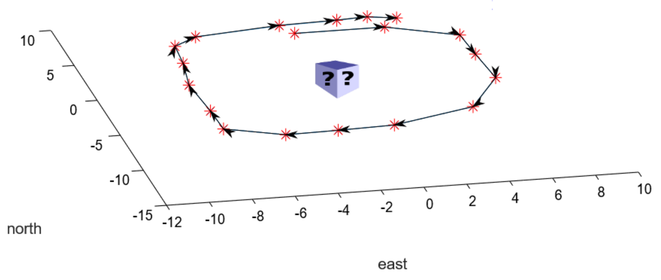
1. Introduction

- **Object Classification** is basic to semantic sensing, required in many robotics applications
- Class measurements differ from geometric: discrete, viewpoint-dependent, correlated
- Need to handle localization error, classification noise, variations in appearance



2. Problem Formulation

- Object of (latent) class $c \in \mathcal{C} = \{1, \dots, N_c\}$
- Mobile robot at time t_k acquires sensor observations $\mathcal{Z}_k$ and user controls $\mathcal{U}_k$
- Given history up to time index k, infer class c



$$b[c_k] \doteq \mathbb{P}(c \mid \mathcal{H}_k) = \mathbb{P}(c \mid \mathcal{Z}_{0:k}, \mathcal{U}_{0:k-1})$$

3. Contributions

Scheme for fusing classification measurements

Model **correlation among viewpoints**

To prevent over-weighting of individual classifications

Localization uncertainty

For robustness to navigation errors

Model uncertainty

For robustness when faced with challenging data

4. Spatial Class Model

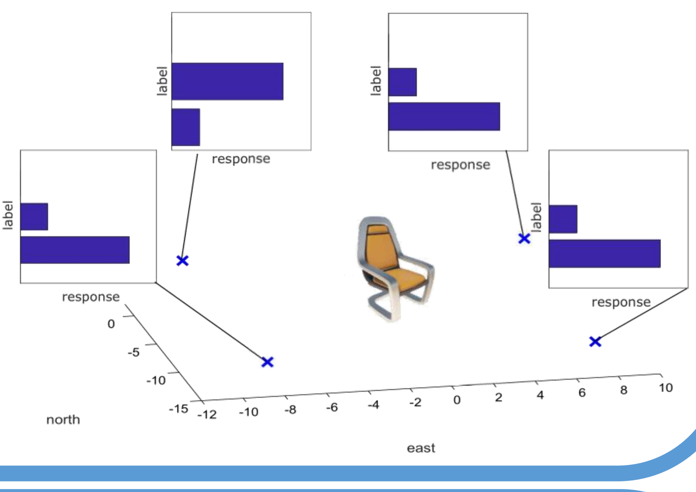
For every known class c, model similar to Teacy et al, 15'

$$s = f_c(x^{(rel)}) + \epsilon$$

$$f_c(x^{(rel)}) \sim \mathcal{GP}\left(\mu_c(x^{(rel)}), k_c(\cdot,\cdot)\right)$$

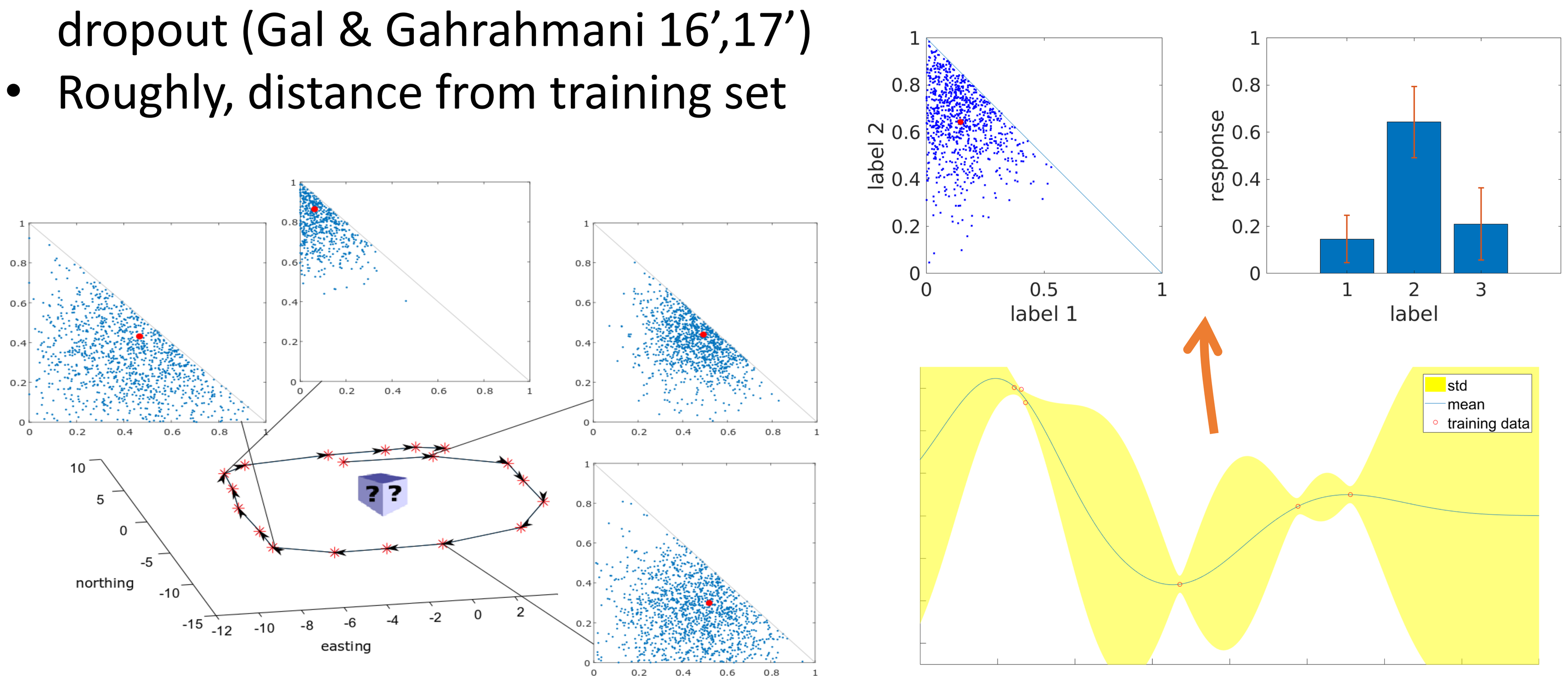
Inducing joint distribution

$$\mathbb{P}(\mathcal{S}_{0:k} \mid c, \mathcal{X}^{(rel)}_{0:k}) = N\left(\mu_{0:k}, \Sigma_k\right)$$



5. Model Uncertainty

- Approximate posterior $\mathbb{P}(s \mid z)$ using multiple forward passes with dropout (Gal & Gahrahmani 16',17')
- Roughly, distance from training set



6. Approach

$$\mathbb{P}(c \mid \mathcal{H}_k) = \int_{\mathcal{X}_{0:k},o} \underbrace{\mathbb{P}(c \mid \mathcal{X}_{0:k}, o, \mathcal{H}_k)}_{(a)} \underbrace{\mathbb{P}(\mathcal{X}_{0:k}, o \mid \mathcal{H}_k)}_{(b)} \, d\mathcal{X}_{0:k} do$$

Marginalize over last classification

$$\frac{1}{n_k} \sum_{s_k \in \mathcal{S}_k} \mathbb{P}(c \mid s_k, H_k \setminus \{z_k\})$$

Marginalize over Landmarks

$$\int_{\mathcal{L}} \mathbb{P}(\mathcal{X}_{0:k}, o, \mathcal{L} \mid \mathcal{H}_k) \, d\mathcal{L}$$

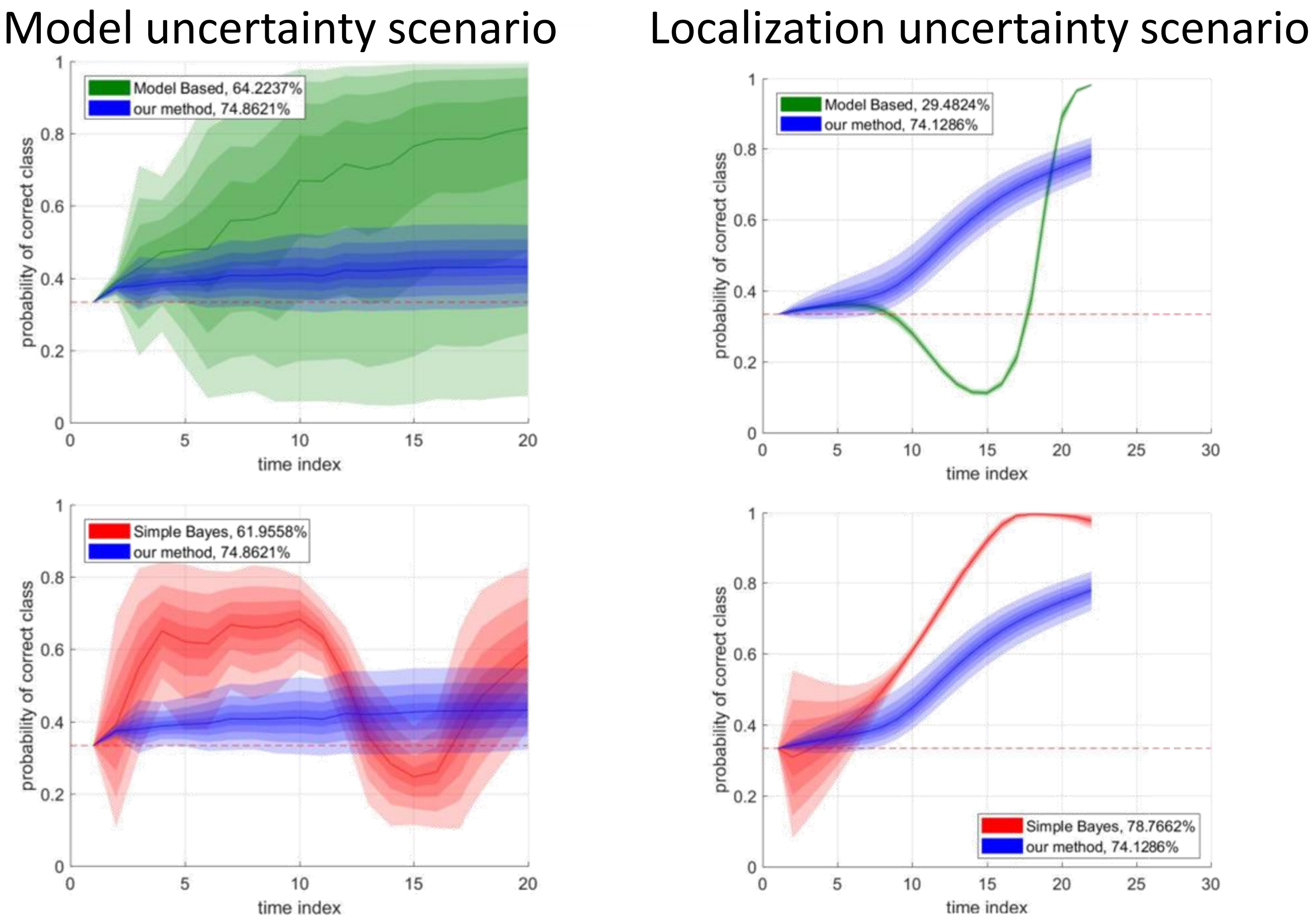
After applying Bayes, marginalization over past classifications:

$$\mathbb{P}(s_k \mid c, H_k \setminus \{z_k\}) = \int_{\mathcal{S}_{0:k-1}} \underbrace{\mathbb{P}(s_k \mid c, \mathcal{S}_{0:k-1}, \mathcal{X}^{(rel)}_{0:k})}_{\text{Class model}} \cdot \underbrace{\prod_{i=0}^{k-1} \mathbb{P}(s_i \mid z_i)}_{\text{Model uncertainty}} \, d\mathcal{S}_{0:k-1}$$

7. Results – MATLAB Simulation

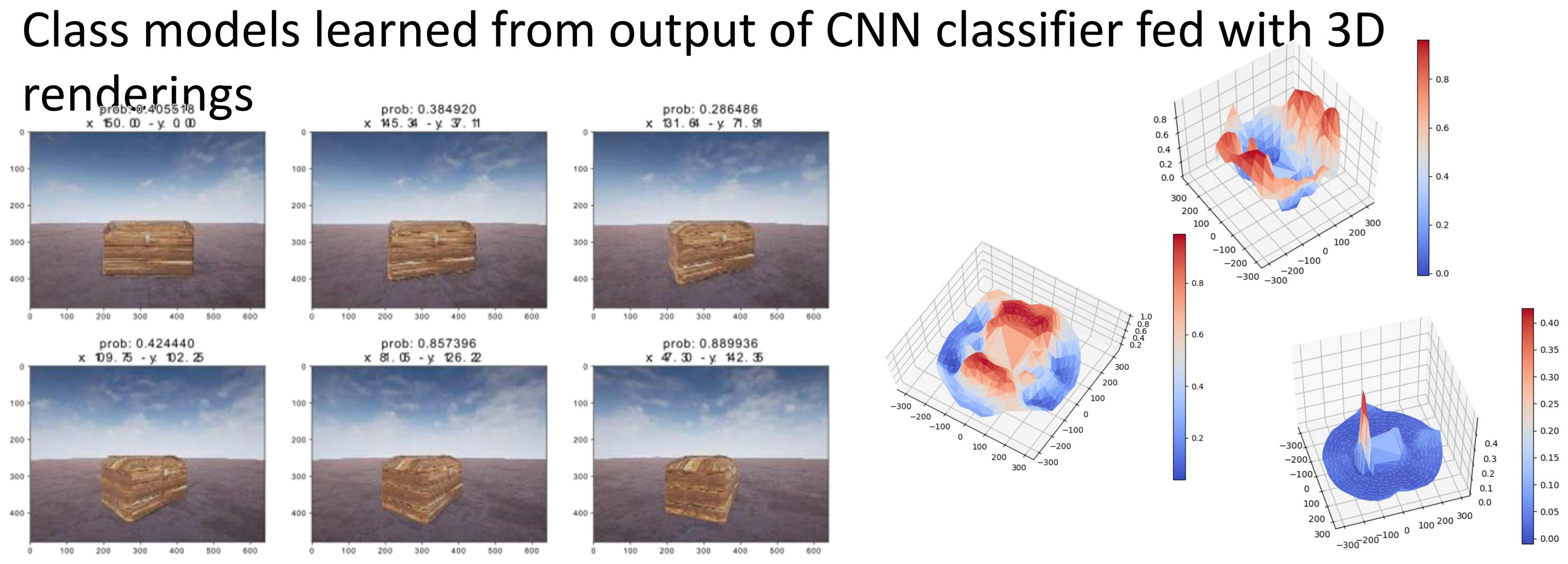
Statistics of probability of correct class, **our method** against **Model Based** (as in Teacy et al. 15') and **Simple Bayes**. One step in color intensity corresponds to 10% percentile step.

Model uncertainty scenario | Localization uncertainty scenario

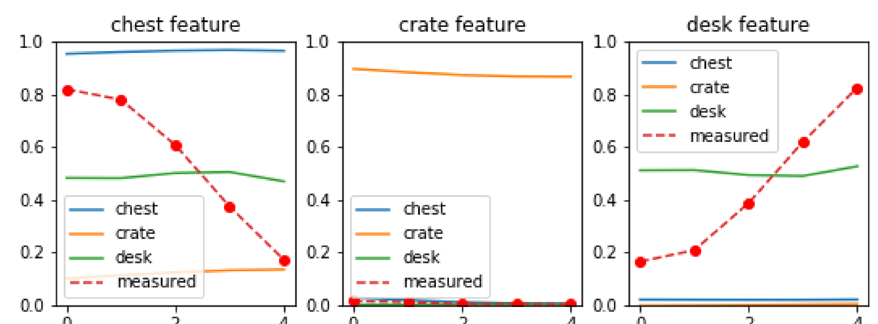


8. UE Evaluation (Under way)

- Class models learned from output of CNN classifier fed with 3D renderings



- As in synthetic scenarios, localization error introduces class aliasing



- Evaluation in scenarios with varying localization error and with model uncertainty is under way

9. Conclusions

- Developed method for accounting for model and localization uncertainty benefits robust classification in synthetic simulation.
- Similar properties are currently investigated in a more realistic setting.