

CONTRIBUTIONS

- 1. Formal definition of "Open World Recognition", which extends the existing definition of Open Set Recognition defined for static notion of set.
- 2. A recognition system that can continuously learn new incoming categories in an open world model.
- 3. We show that thresholding sums of monotonically decreasing functions of distances of linearly transformed feature space can have arbitrarily small "open space risk".
- 4. Open World Evaluation Protocol



solution to Open World Recognition is a tuple $[F, \varphi, \nu, L, I]$

- 1. F(x) is a multi-class open set recognition function
- 2. $\varphi = [f_1(x), \ldots, f_k(x)]$ vector function of per-class recognition functions
- 3. $\nu(\varphi) : \mathbb{R}^i \mapsto [0, 1]$ is a novelty detector (to determine if the class is known/unknown)
- 4. L(x) is labeling process applied to novel unknown data
- 5. $I_t(\varphi, D_t)$ is an incremental learning function to scalably learn and add new measurable recognition functions to φ

Ideally, all of these steps should be automated, but herein we presume supervised learning with labels obtained by human labelling.

Caltech 256 time **RELATED WORK**



Towards Open World Recognition

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A recognition system in the "open world" has to continuously update with additional object categories and be robust to unseen categories and have minimum down-



OPEN SPACE



Let Open Space is the space sufficiently far from any known positive training sample $x_i \in \mathcal{K}, i = 1 \dots N$, be defined as:

$$\mathcal{O} = S_o - \bigcup_{i \in N} B_r(x_i) \tag{1}$$

Then probabilistic **Open Space Risk** $R_{\mathcal{O}}(f)$ for a class ycan be defined as

$$R_{\mathcal{O}}(f_y) = \frac{\int_{\mathcal{O}} f_y(x) dx}{\int_{S_o} f_y(x) dx}$$
(2)

Given an empirical risk function $R_{\mathcal{E}}$, the objective of Open Set Recognition is to find a measurable recognition function that manages (minimizes) the Open Set Risk:

 $\operatorname{argmin} \{R_{\mathcal{O}}(f)\}$

OPENING AN EXISTING ALGORITHM

Theorem 1: Open Space Risk for Model Combination



Theorem 2: Open Space Risk for Transformed Spaces



$$+\lambda_r R_{\mathcal{E}}(f)\}$$

NEAREST NON-OUTLIER ALGORITHM

Nearest Class Mean Classifier: Assign an image *i* to the class closest to the class mean by $\mu_k = \frac{1}{|\mathcal{I}_k|} \sum_{i \in \mathcal{I}_k} x_i$. Then class conditional probabilities are given by \int_{∞}^{∞}

$$p'(c|x) = \frac{1}{Z} exp(x^T W^T W \mu_c + s_c)$$

where Z denotes the normalizer and s_c is a per class bias.

Nearest Non-Outlier Algorithm: Let $W \in \mathbb{R}^{d \times m}$ be the linear transformation dimensional reduction weight matrix (metric learning phase). Then given τ , let

$$\hat{f}_i(x) = \frac{\Gamma(\frac{m}{2} + 1)}{\pi^{\frac{m}{2}}\tau^m} (1 - \frac{1}{\tau} \| W^{\top} x - W^{\top} \mu_i$$

be our measurable recognition function with $\hat{f}_i(x) > 0$ giving the probability of being in class.







Experiment Details

- 1. Dataset: ILSVRC'10 (and '12): 1.2M training images, 1K classes
- 2. Features: Dense SIFT features quantized in 1000 BoW
- 3. Algorithms: Nearest Class Mean Classifier, Nearest Non-Outlier Algorithm, 1vsSet, Linear SVM
- . Training Phase:
 - Parameter Learning with initial set of categories, followed by estimation of τ to balance open space risk
- Incrementally add categories
- 5. Testing Phase: Test with known and unknown categories

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