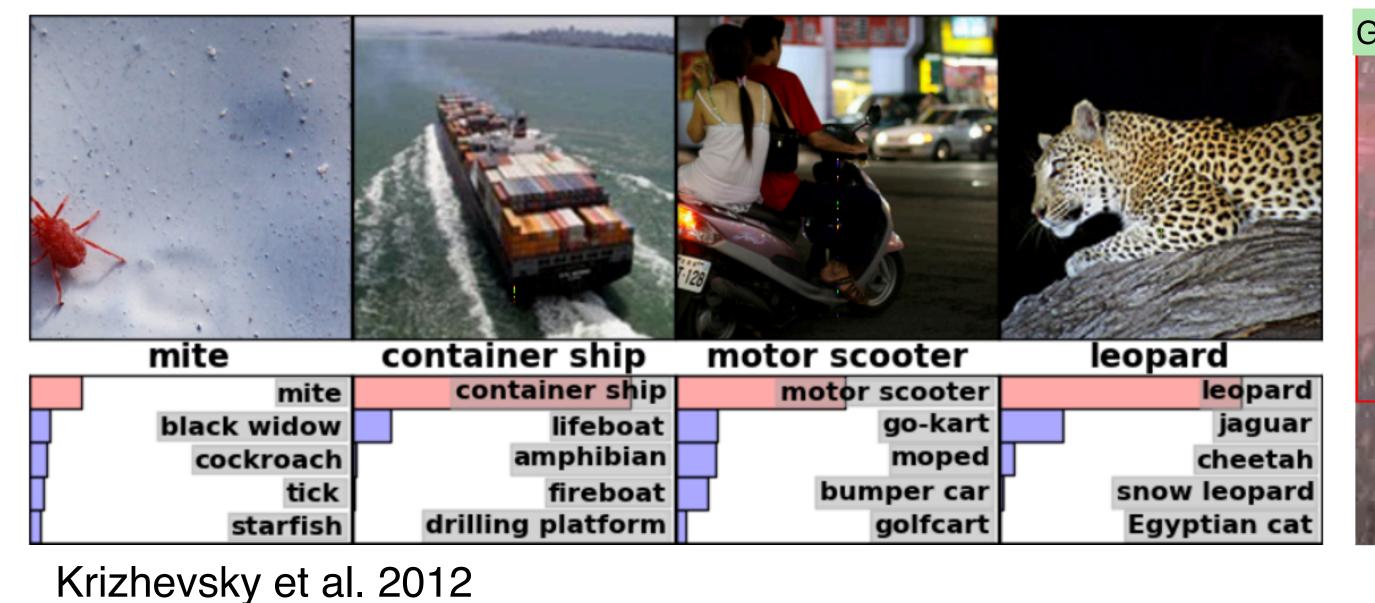


Multi-Class Open Set Recognition Using Probability of Inclusion

Overview

The perceived success of recent visual recognition approaches has largely been derived from their performance on classification tasks, where all possible classes are known at training time.

ImageNet Classification



Girshick et al. 2014

Even with state-of-the-art representation learning, results are disappointing for open set recognition, where the possibility of encountering classes not present during training exists in testing:

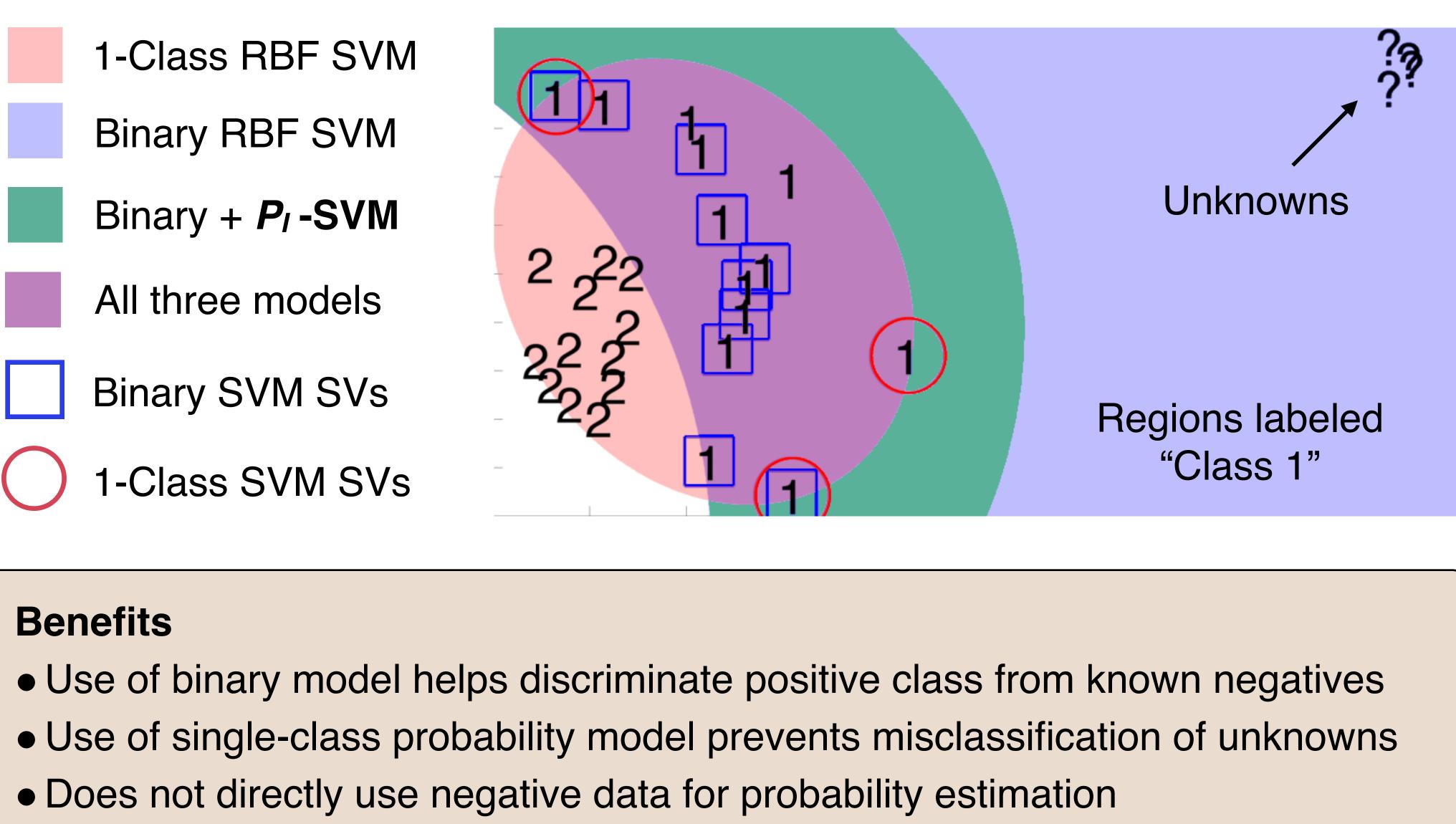
- ILSVRC2014 Best Classification Result: 6.66% Error Rate
- ILSVRC2014 Best Detection Result: **43.9 mean AP**

How can supervised learning directly address open set recognition?

Previous Approaches	Drawbacks
Novel Class Detection	No multi-class recogn
Outlier Rejection	Works with same training/testing
Sigmoid Calibration	Sigmoid function often the w

Proposed Approach: fit a robust single-class probability model over the positive class scores from a discriminative binary classifier

- 1-Class RBF SVM Binary RBF SVM Binary + *P*₁-SVM All three models Binary SVM SVs
 - 1-Class SVM SVs



Benefits

- Use of binary model helps discriminate positive class from known negatives
- Does not directly use negative data for probability estimation
- Does not assume any particular distribution over all scores
- Fast and easy to compute

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ImageNet Detection



nition ng backgrounds wrong model

The P₁-SVM Algorithm

Objective: compute a per class unnormalized posterior probability estimate for any input sample.

Observation: probability calibration is well-defined near a decision boundary; **extreme value theory** can be invoked to model the probability of inclusion P_I

$$P_I(y|x,\theta_y) = \xi \rho(y) P_I(x|y,$$

EVT params. constant (1)

 $y^* = \operatorname{argmax} P_I(y|x, \theta_y)$

P_l-SVM Training

- Train a 1-vs-Rest RBF SVM h(x) for a set of known classes
- 2. For each class:

 - Estimate size of tail for sorted scores near the decision boundary
 - . Fit a Weibull distribution to the tail

P_l-SVM Probability Estimation

- 1. For each input sample:
 - Generate a score for each known class using h(x)

How can we estimate the tail size for Weibull fitting?

Consider points within distance ϵ of the SVM decision boundary as extrema

$$B^{+}(x;\epsilon) = \begin{cases} 1 & \text{if } h(x) \leq \epsilon \\ 0 & \text{otherwise} \end{cases}$$

Cross-Class-Validation for Open Set Evaluation

Closed set testing on MNIST λο 0.85 0.7 1-vs-Rest SVM 0.55 (6, (1, (8, (9), (0), (0)))(# training classes, # testing classes)

of digits (0-5)

0	0	0
1	۱	ł
2	Э	г
3	3	3
Ч	4	Ч
5	ح	5

Simulate unknown classes of open set recognition by defining number of:

