A Classification Framework for Open Set Domains

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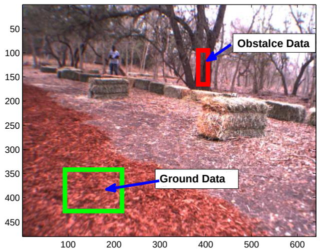
Introduction: Problems in Artificial Intelligence (and Machine Learning) can be divided into *Open Set* and *Closed Set* subtypes. *Closed Set* domains assume that all types, or classes, of a domain have been seen. In contrast, *Open Set* domains assume that new types (classes) may be encountered.

Most classifiers address *Closed Set* domains. Specifically, when they make classification decisions, they implicitly assume that the unknown instance is drawn from classes seen in the learning set. However, the general AI problem falls into the *Open Set* category. If an intelligent agent is ever to function in real human environments (whether digital, as in the web, or physical as in Robotics), it must predict when a new class is being seen for the first time. As a trivial *future* example, if the robot is putting away clothing it has just washed, and there is a new dress in the wash never before seen by the robot, the robot should know that this dress is something new and that a human needs to be consulted before it knows where the dress should be stored.

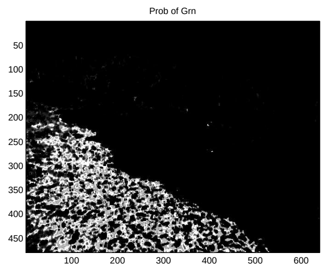
Arguments can be made that true Artificial Intelligence cannot be achieved without some viable solution to the *Open Set* Problem, because an intelligent system should not blindly act unless it is confident that the action is appropriate. A key theoretical ingredient for formulating a solution to the *Open Set* Problem, is a paradigm for *Deciding When to Abstain* from make a prediction. Given such a paradigm, and agent can begin to make such decisions as "I must *learn* more about this situation before acting." In this presentation we describe such a framework, which we demonstrate working on an unsolved Robotics problem [4, 2], as well as on standard multi-class data sets (such as the MNIST digits data).

Mathematical Formulation: The proposed Classification Framework for *Open Set* Domains is based on a new density framework which starts by projecting high dimensional data into a high order (32^{nd} order or higher is possible) polynomial space that *preserves the interaction between all polynomial terms* (this is not true for the commonly used Polynomial Kernels in SVMs). These polynomial projections are non-local (unlike Gaussian Kernels, or Mixture of Gaussian models) which potentially addresses the curse of dimensionality problem [1], and are based on the Polynomial Mahalanobis distance metric described in [3].

Experimental Results: As an example of the inadequacy the current state of the are Machine Learning algorithms in dealing such *Open Set* Problems, consider the image in Figure 1(a), which has been labeled with ground (or traversable parts of the image) and obstacle (or non-traversable parts of the image). Figure 1(b) shows an "adequate" labeling of traversable ground and Figure 1(c) shows an "adequate" labeling of obstacles. The black areas of these two figures indicate that, based on the labeled data in Figure 1(a), no conclusion can be made about these parts of the image. By "adequate" labeling, we refer to the fact that the labeled areas of these images are similar to the original labeled areas in Figure 1(a), and that labels have not been assigned to parts of the image that are dissimilar to the labeled images in Figure 1(a). These "adequate" classifications given in Figure 1(b) and Figure 1(c) are obtained using the algorithm which will be described in this presentation. While the other images in Figure 1 show results obtained using three state of the art Machine Learning algorithms: Parzen Windows [6] (AlgB), Manifold Parzen Windows [6] (AlgC), and Support Vector Machines with the outputs probabilistically scaled [5] (AlgD). Note that these algorithm fail to capture the notion of "I don't know and therefore cannot make a prediction", which is a key component of classification in *Open Set* domains. As an example, these algorithms label objects such as hay bales as traversable,

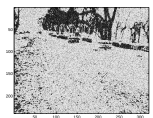


(a) Labeled Image

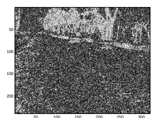


(b) AlgA GRN.

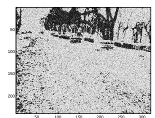
(c) AlgA OBS.



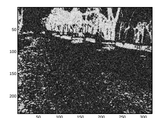
(d) AlgB GRN.



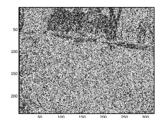
(e) AlgB OBS.



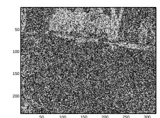
(f) AlgC GRN.



(g) AlgC OBS.



(h) AlgD GRN.



(i) AlgD OBS.

Figure 1: *Image Based Robot Navigation Data. Pure black in the labeled images indicates that the model doesn't know, and is making NO prediction.*

even though no training examples of this type are given to these algorithms, and hay bales are NOT traversable. This presentation will elaborate on why these algorithms failed, as well as present results on standard multi-class data sets (such as the MNIST digits data).

References:

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Topic: Open Set Classification Problems.
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