A Closer Look at Unknown Recognition

Sarthak Jain
Los Gatos High School
jainsarthak101@gmail.com

Shu Kong
Texas A&M University
shu@tamu.edu

Abstract

Computer Vision models often face imagery data that is from unknown classes that are not seen in the training set. To recognize such unknown images, previous research has created algorithms that exploit labeled data w.r.t K categorical classes. In particular, the state-of-the-art method MaxLogits uses the maximum value of the logits to measure the open-set likelihood, while OpenGAN learns a discriminator as the open-set likelihood function by learning with generated fake open-set training data. In our paper, we compare OpenGAN and MaxLogits in scenarios that we have large and small numbers of classes. We then study their performance on three different types of unknown data: Gaussian noise, uniform noise, heavily-perturbed images, unseen images from other datasets. Experiments show that OpenGAN outperforms MaxLogits in almost all unknown types.

1. Introduction

The training set for learning a visual recognition model will not represent the entire world. As a result, testing data from novel classes unseen during training might cause catastrophic failures for the learned visual recognition model. We call such unknown data (from never-before-seen classes) *open-set* [6].

To recognize unknowns vs. known examples, one usually train a binary classifier as an open-set likelihood over the closed-set train-set and an outlier set (i.e., open-set train-set). The oulier set contains data from classes that are disjoint to those in the closed-set train-set. The binary classifier can be built on a deep neural network which outputs a single score as the open-set likelihood to classify the input data into known vs. unknown. However, one issue with this approach is that the binary classifier tends to overfit to the outlier set, therefore struggles when faced with real-world testing data that is not similar to either close-set training or outlier training data [2].

A recent approach, MaxLogits, entails training a K-way classifier network on the closed set. The logits of a K-way classification network can be used to measure the likelihood of an input image being classified as unknown vs known. Another approach, OpenGAN [3], utilizes a Generative Adversarial Neural Network [1] to train a discriminator as the open-set likelihood function to classify an input image into known vs. unknown. OpenGAN operates in the feature space defined by the K-way classification network. It is worth noting that OpenGAN learns to generate "fake" open-set data to augment the outlier set, hence learns better a binary classifier (i.e., the discriminator) for recognizing unknowns.

Unknown data can appear in various types such as images from novel classes, images of random noises, images with heavily perturbations, images from out-of-domain data, etc. In this paper, we strive to study unknown recognition with various types of unknown data. We particularly focus on the aforementioned two methods, MaxLogits and OpenGAN through extensive experiments. We conclude that OpenGAN outperforms MaxLogits in almost all unknown types.

2. Methodology

We focus on two recent state-of-the-art methods below. **OpenGAN** generates its own outlier set that approaches the likeness of the closed-set. OpenGAN also utilizes an auxiliary outlier set for training. Unlike traditional GANs, however, OpenGAN trains on the features collected from a K-way classification and generates features. The K-way classification network has already been trained on the closed-set. Then the feature generator is trained in tandem with the feature discriminator with closed-set image features being given the label of 1 while open-set image features and generated features are given the label of 0. **MaxLogits** is a different application of the K-way classification network. It takes the raw logits of the output K nodes of a K-way classifier and uses those values as an indicator of which an image is closed-set or open-set.

3. Experiment

3.1. Protocols

We evaluated OpenGAN and Max Logits when trained on datasets with high K classes and low K classes. The high K classes dataset we used was tinyImageNet [4]. The train set we used consisted of the first 180 classes of tinyImageNet. The low K classes dataset we used was CIFAR. We used the first 6 classes of CIFAR.

The Out of Distribution images were selected to be disjoint from ImageNet and as a result disjoint from tinyImageNet and CIFAR which are categorical subsets to ImageNet. Below is a list of every single out of distribution dataset that was used for evaluation along with an explanation to justify its inclusion.

- **Cross-Dataset Evaluation**: For the semantically different evaluation datasets, we used test SVHN [5] and a three channel concatenated test MNIST. Both Datasets measure how well a model would distinguish a data set semantically different than the train-set as out of distribution.

- **Gaussian or Uniform Noise Evaluation**: For the noise datasets, we used images entirely made of pixels randomly sampled from Gaussian and Uniform noise distribution. This created dataset served to test a model's accuracy when put up against images with no features at all. Since both Max Logits and OpenGAN utilize a K-way classification backbone to extract features, such an evaluation would test if these algorithms efficacy dependence on the presence of such features.

- **Noise as Unknown**: For feature containing data sets with noise, we took images from the test version of the closed-set (tinyImageNet) and added a pair of strong or weak transforms to those images. The light transform consisted of Enhance Contrast and Gaussian Blur while the dark transform consisted of Flipping, Enhance Contrast, a stronger Gaussian Blur, and Rain transform. Its inclusion is to test how well models can distinguish if an image might have a lot of noise despite being the same class as an image from the train set. Models that perform well on this dataset serve to be well used when images taken from a system like an autonomous vehicle may not contain any unknown objects but are still significantly different to the images and feature composition of the train-set.

3.2. Metrics

The two metrics we report are Area Under Precision Recall Curve (AUPR) and Area Under Receiver Operating Curve (AUROC). Both these metrics are ranking based evaluation systems that have been used by previous Open-Set Recognition work. **AUPR** is the probability that a point listed above a positive classified point is also positive. **AUROC** measures the performance of a binary classifier across varying confidence thresholds. The test closed-set dataset for both OpenGAN and MaxLogits models consisted of an unseen version of the initial closed-set (so either test CIFAR or test tinyImageNet depending on what the OpenGAN or MaxLogits model was trained on). Depending on the protocol, the test open-set model changes (See 3.1).

3.3. Implementations

Every K-way Model and OpenGAN model was trained using only one GPU. **The K-way model for tinyImageNet** was trained with 50 epochs. For training this K-way model we utilize Stochastic Gradient Descent with a learning rate of 0.003, weight decay of 0.0005, and momentum of 0.9. We also utilize a Lambda learning rate scheduler with the lambda following cosine. Since we have 180 classes taken from out tinyImageNet dataset, this K-way model has 180 output nodes. The augmentations that were used for the training data were random cropping and random horizontal flipping.

The OpenGAN model for tinyImageNet used the aforementioned trained K-way model to collect features from an input image. Then the Discriminator and Generator of the OpenGAN were trained for 20 epochs. For training the OpenGAN, we had two optimizers: one for the Generator and one for the Discriminator. The Generator optimizer has a base learning rate of 0.0001 while the Discriminator's learning rate is a 0.0001/1.5. The OpenGAN was trained on both the testTinyImagNet and the SVHN dataset (train open-set dataset). The testTinyImageNet was given the same transforms as when it was used for training the K-way classifier. The SVHN dataset was randomly horizontally flipped and resized.

3.4. Results

When using a high class dataset (K = 180) for training. OpenGAN usually outperforms Max-Logits as an open-set recognizer. For Cross-Dataset Evaluation OpenGAN has better AUPR and AUROC for the test cases of SVHN vs testTinyImageNet and EuroSAT vs tinyImageNet. However, for MNIST (where grey scale channels are cloned into 3 channels) vs Tiny, Logits has better AUPR and AUROC. However, the MaxLogits performance is very close to a random 50/50 guess indicating both our trained OpenGAN and MaxLogits are not suited for this classification task. For the Noise evaluations, OpenGAN performed significantly better than Max-Logits when tested with Gaussian Noise and Uniform Noise. Finally for the Noise as Unknown, OpenGAN again outperforms Max Logits in both heavy transforms and light transforms.

Table 1. The closed-set dataset was testTinyImageNet. K-way model pretrained on ImageNet and Finetuned on trainTinyImageNet. The outlier-set was trainSVHN (AUROC / AUPR).

open-set	**MaxLogits**	**OpenGAN**
SVHN	26.19 / 40.12	**99.97 / 99.97**
EuroSAT	82.18 / 84.40	**94.85 / 94.86**
MNIST	**54.46 / 55.86**	22.20 / 38.43
Normal Noise	20.57 / 44.13	**100.0 / 100.0**
Uniform Noise	26.90 / 46.20	**77.89 / 84.02**
Transforms 1 (heavy)	64.56 / 67.72	**87.37 / 83.20**
Transforms 2 (light)	57.73 / 57.72	**68.89 / 62.10**

When using a low class dataset (K = 6) for training, OpenGAN still generally outperforms Max-Logits. For Cross-Dataset Evaluation, OpenGAN again had a larger AUROC and AUPR than Max-Logits for SVHN and EuroSAT evaluation. However, interestingly for MNIST Max-Logits massively outperforms OpenGAN which is similiar to our results when K = 180. This suggests a motivation of creating an ensemble between Max-Logits and OpenGAN. Also similiar to the high class case, OpenGAN has a better AUROC and AUPR than MaxLogits for both the noise evaluations. For the Noise as Unknown Evaluations, OpenGAN again outperforms Max-Logits for both heavy and light transforms.

Table 2. The closed-set dataset was testCIFAR. K-way model pretrained on ImageNet and Finetuned on trainCIFAR The outlier-set was trainSVHN (AUROC / AUPR).

open-set	**MaxLogits**	**OpenGAN**
SVHN	67.07 / 74.91	**89.18 / 88.37**
EuroSAT	77.60 / 84.05	**93.27 / 94.91**
MNIST	**93.41 / 94.43**	35.74 / 47.55
Normal Noise	80.90 / 85.75	**98.78 / 98.93**
Uniform Noise	71.16 / 81.79	**94.6 / 96.93**
Transforms 1 (heavy)	65.48 / 69.46	**75.62 / 71.77**
Transforms 2 (light)	56.31 / **56.95**	**57.78** / 54.60

4. Discussion and Future Work

Through various evaluations, we exemplify that OpenGAN generally outperforms MaxLogits on both Gaussian and Uniform Noise Evaluations and Noise as Unknown Evaluations irrespective of the whether it was trained on a high class (K = 180) or low class (K = 6) dataset. However, the benefit you get from OpenGAN is increasingly pronounced when using a high class dataset; therefore, suggesting that OpenGAN benefits from higher classes compared to MaxLogits. For Cross-Dataset Evaluation, The results were a little more mixed. OpenGAN outperformed MaxLogits on SVHN (train version was also the outlier set) and on EuroSAT; however, it did not outperform MaxLogits on MNIST for both K=180 and K=6. Therefore, this suggests that an ensemble network that combines the insight of MaxLogits and OpenGAN would be a more ideal solution to perform better in Cross-Dataset Evaluation tasks and area of future work.

One possible limitation is that we did not follow the standard open-set recognition literature that does not pretrain models, instead, we use pretrained models finetuned for closed-set recognition (although we guarantee that pretraining-set and the closed training set have disjoint classes). In the future, we plan to compare the results with and without pretraining.

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