Novelty-based Generalization Evaluation for Traffic Light Detection

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Abstract—The advent of Convolutional Neural Networks (CNNs) has led to their application in several domains. One noteworthy application is the perception system for autonomous driving that relies on the predictions from CNNs. Practitioners evaluate the generalization ability of such CNNs by calculating various metrics on an independent test dataset. A test dataset is often chosen based on only one precondition, i.e., its elements are not a part of the training data. Such a dataset may contain objects that are both similar and novel w.r.t. the training dataset. Nevertheless, existing works do not reckon the novelty of the test samples and treat them all equally for evaluating generalization. Such novelty-based evaluations are of significance to validate the fitness of a CNN in autonomous driving applications. Hence, we propose a CNN generalization scoring framework that considers novelty of objects in the test dataset. We begin with the representation learning technique to reduce the image data into a low-dimensional space. It is on this space we estimate the novelty of the test samples. Finally, we calculate the generalization score as a combination of the test data prediction performance and novelty. We perform an experimental study of the same for our traffic light detection application. In addition, we systematically visualize the results for an interpretable notion of novelty.

I. INTRODUCTION

In recent times, machine learning models are increasingly deployed for several real-world applications [27]. This has led to the development of several Convolutional Neural Network (CNN) architectures. It is a common practise to compare the CNNs based on their generalization ability. Generalization in computer vision and machine learning is defined as "the ability of image and video processing algorithms such as object detectors or classifiers to perform well not only on the dataset they are trained on, but also on novel data [11]." Hence, the generalization of the developed networks are based on their performance on a test dataset that is independent of the training data [15]. However, such an independent dataset is often chosen randomly. A random selection does not ensure that the test subset has novel samples. In AD application, we acquire data from several video streams at regular intervals [27]. In principle every image in the stream is independent from the training dataset. However, for generalization evaluation it is necessary to gauge the network’s performance on novel images that the network did not see during the training. Hence, we introduce a second criterion, i.e., novelty of the objects in the image, to weigh the network’s performance.

Given a training dataset, a test sample is deemed novel when they are anomalous w.r.t. it [9]. Such anomalous samples do not conform with the general properties of the majority of the training samples and are present in the low density regions of the training dataset. Therefore, the anomalous samples are not to be confused with mislabelled data. The terms outlier and novelty detection are synonymous to each other because they both detect samples that are anomalous. In fact, few works categorize both outlier and novelty detection as anomaly detection [28] and outlier detection methods have been applied for novelty detection in several cases [6], [9], [17], [20], [24]. The underlying difference between them lies in the step that follows detection. The former aims at eliminating the detected anomalies, whereas the latter aims to identify new samples (w.r.t. a normal dataset) from the data [23]. Although the occurrence of novel samples may be infrequent in comparison to regular samples, evaluating the CNNs performance on them is not a trivial task [24]. Such evaluations are important in AD applications to understand the limitations of a CNN prior to deployment. Nevertheless, the major challenge for novelty-based generalization is the magnitude of the AD datasets, i.e., they consist of several thousands of images with multiple objects. Evaluating the novelty of each image in the test dataset w.r.t. all training images based on manually defined properties, e.g., brightness, blurriness, is tedious [16], [27].

We address this challenge by using the representation learning method, i.e., Variational Auto-encoders (VAE) [5], to extract the key features of the dataset, i.e., latent dimensions. Given a dataset of size \(N \times H \times W \times C\), where \(N\) is the number of images, \(H\) is its height, \(W\) is its width and \(C\) is the number of channels, the VAE reduces this to a \(N \times d\) space, where \(d\) is the number of latent dimensions. It is on this low-dimensional latent representations we perform our novelty assessment. By this way, we avoid the need to perform and one-to-one comparison between the train and test data. Finally, we score the generalization of a CNN by rewarding its ability to perform well on the high novel samples. Few existing works apply representation learning, e.g., Auto Encoders (AE), to identify novel samples based on the reconstruction errors [7]. However, over several iterations AE reduces the reconstruction error of the novel samples as well and may not be directly applicable for novelty estimation [2]. Hence, we use them only as a dimensionality reduction framework. We prefer a VAE instead of an AE because the representations of an AE are not continuous. Whereas in case of a VAE, the latent representation being mean value of a distribution can be varied.
to understand the physical meaning of that dimension. This property is essential for human interpretation of novelty [14].

Existing works target on enhancing the CNN generalization during the training process by regulating several factors such as number of training iterations, learning rate, batch size and regularization [13], [15], [31]. But to the best of our knowledge, there are no existing KPIs (Key Performance Indicator) that quantify the generalization ability of a fully trained CNN.

In this work, we propose a two step framework to quantify the generalization ability of a CNN. In the first step we reduce the dimensionality of the training and test dataset using a VAE. In the second step we estimate the novelty of a test sample by evaluating its likelihood that it belongs to the training data. Finally, the prediction performance of a CNN on a given test sample is weighted by the novelty of the test sample to obtain a single generalization score. Moreover to ensure interpretability of the novelty scorer, we visualize its results and present a more human-understandable notion of novelty. The primary contributions of this work are,

- A generalization scoring measure based on representation learning and novelty detection algorithm.
- Performance comparison of various novelty detection algorithms from different paradigms.
- Generalization evaluation experiments on different CNN architectures for traffic light detection problem in the AD domain.
- Interpretation of novelty using the latent representations learnt by the VAE.

II. RELATED WORK

Novelty detection literature is broadly grouped into classification, e.g., One-Class Support Vector Machines (OCSVM), Nearest Neighbor, e.g., Local outlier factor (LOF), clustering, e.g., k-Nearest Neighbors (kNN) and statistical based approaches, e.g., Histogram-based outlier score [4], [12], [21], [24], [26]. The works of [20], [24] provide a brief summary about the novelty scoring taxonomies and algorithms. As the scoring algorithms suffer from the curse-of-dimensionality, it is often preceded by a feature extraction or dimensionality reduction step [8].

As a classification-based approach, the work of [6] applies OCSVM for monitoring novel patterns in sensor data. They firstly extract statistical features from various sensors, which are then passed on to OCSVM for novelty scoring. Instead of feature extraction, the work of [18] performs dimensionality reduction using Principal Component Analysis [13] before using OCSVM. Likewise, the work of [17] extracts the word usage patterns from documents to score the novelty of patents using LOF [4]. The work of [21] uses kNN novelty detection on data streams to learn the boundary of the training data. The test sample novelty is based on its distance from the trained boundary. Histogram based outlier score (HBOS) is a simple combination of uni-variate methods applied to multiple dimensions [12]. Although, they do not account for dependence between variables, its efficiency on large datasets

is an advantage. Similarly, Lightweight Online Detector of Anomalies (LODA) [25] uses an ensemble of one-dimensional histograms for novelty detection. The work of [25] applies it for novelty detection in data streams. The work of [9] uses LSTM-AE to reduce the discrete sequences into latent representations. During testing, the test data samples are reduced into the latent representations and fed as input to the Isolation Forest [19]. The Isolation Forest is advantageous as they are unsupervised and isolate the novel data points without the need of normal data.

Unlike the straightforward AE reconstruction error based novelty scorer [7], the work of [2] introduces likelihood of a test sample in addition. Similarly, the work of [1] applies a likelihood ratio test for evaluating the novelty of the video sequences based on predefined normal data. The q-space novelty detection method [29] proposes several novelty scoring methods using the VAE latent feature and original space. One of them quantifies novelty by estimating the likelihood of a test sample belonging to the modeled latent space distribution of the normal data. In contrast to aforementioned methods, we apply the novelty detection on image datasets in the context of CNN generalization evaluation. Moreover, we experimentally present a systematic performance comparison of various novelty scoring approaches. Secondly, we do not use the AE reconstruction error as a novelty score and rather use VAE only for dimensionality reduction. Although, we estimate novelty based on likelihood of the test sample as done in the work of [2], we additionally visualize novelty on the latent and the image space. That is, we provide an interpretable notion of novelty rather than mere reporting of scores.

III. OUR FRAMEWORK

Our generalization evaluation framework involves three phases, viz., pre-processing, representation learning and novelty scoring. We explain each of them using traffic light (TL) localization CNN from our Autonomous Driving (AD) application. Our framework aims to score the generalization ability of the trained traffic light detectors. Given a traffic scenario image for the task of TL detection, it contains several irrelevant information or objects and evaluating their pixel-wise novelty is inefficient and less insightful. Hence, similar to...
the work of [14], we start with the pre-processing phase where the objects of interest, i.e., traffic lights, are cropped from the train and test datasets. On one hand, the pre-processing phase reduced the size of the images by targeting the object-of-interest $I$. On the other hand, pre-processing phase will increase the number of images because each traffic scenario may have more than one TL object and each of them is extracted as a separate image. For example, the Bosch Small Traffic light dataset and the subset of DriveU dataset we use has $\approx 10k$ and $50k$ traffic lights in the training data [3], [10]. Hence, we pass the TL crops to the representation learning phase to train a Variational Auto-Encoder (VAE) (c.f. Figure 1 4).

The VAE comprises of an encoder, a $d$-dimensional bottleneck layer and a decoder which mirrors the encoder. Using the training data, its objective is to learn a $d$-dimensional latent distributions by optimizing a set of parameters $\phi$ based on the KL-divergence and reconstruction loss. Each dimension is defined by a mean $\mu$ and standard deviation $\sigma$. Hence, a fully trained encoder $e_\phi$ is capable of mapping a TL crop to $d$ mean and standard deviation values. For deeper understanding of VAE, readers may refer to the original work [5]. We use the mean value as a low-dimensional representation of the traffic light crop $I$, $e_\phi : I \mapsto \mu \mid \mu = d$. These representations hold the key properties of the RGB images in a compressed form. For example, we project the $d$-dimensional $\mu$ vector ($d = 32$) into a 2-dimensional space using UMAP [22] and DriveU data in Figure 2. The first observation is that the $\mu$ values cluster themselves based on the color of the lights. Although this work focuses on TL detection and not classification, with Figure 2 we intend to emphasize that the lights of same color may have different properties. That is, each color cluster has both dense and sparse regions. Given a new test image, our target is to compress it to the $d$-dimensional $\mu$ vector and score its novelty w.r.t. the training data. For the sake of completeness, we trained a simple AE over the same dataset. However, we did not observe such clustering of the samples based on colors. Moreover, its latent dimensions were challenging to interpret. Hence, a loss value of a highly novel sample is weighted higher than that of less novel sample. However, it is worth mentioning that we do no ignore the less novel samples. Rather, we only weigh them lower in comparison to the highly novel samples. Therefore, our generalization score is a combination of both high and low novel samples but aggregated with different weights.

IV. EXPERIMENTAL EVALUATIONS

As mentioned in Section III we use two well-known TL datasets, i.e., BSTLD and DriveU for the experimental evaluations. We instantiate the $\mathcal{L}$ with Mean Absolute Error (MAE) because it has fixed upper and lower-bounds $[0,1]$. Our evaluation targets to, (a) compare various novelty scoring algorithms that fits our application, (b) evaluate usefulness of the proposed generalization score $G$ and (c) interpret the notion of novelty for the datasets. We extracted the TL crops from both datasets to train the VAE for 750 epochs, with a batch size of 64, a learning rate of 0.0001, $d=32$ and $\beta = 0.1$.

A. Comparative study

The novelty scorer for the TL objects (crops) is an important part of our generalization framework (c.f. Figure 1 in step 6 and 10). In this section we perform a comparative evaluation of existing methods to identify a scorer that best fits our application. For this, we select seven novelty scoring algorithms from various paradigms (c.f. Section II). As we do not have the ground truth novelty scores for the study, we systematically engineer the datasets for our experiment. First we choose a contamination color, e.g., green TLs, which is removed from the train dataset. We engineer the test dataset such that it contains 10% of the contamination color and 90%
Fig. 3: Novelty algorithms comparative study

of the other colors. The contamination color samples are novel w.r.t. training data in this context because all contamination color samples were intentionally removed from the training dataset. We aim to compare the ability of different novelty scoring algorithms to identify these samples in the test dataset. We use the implementation from PyOD and scikit-learn in our evaluation [30] and the area under ROC curve as a quality metric for our evaluation. As a randomness component is involved in our experiment, we perform the contamination sampling three times and show the standard deviation and average ROC.

In Figure 3, we show the results on BSTLD [3] and DriveU [10] dataset with green and red as contamination colors respectively. Amidst the chosen scorers, LOF was the best performing (largest ROC score), followed by the KDE. However, with increase in the number of contamination (novel) samples, we observed that number false positives (normal samples identified as novel) increased more for LOF in comparison to KDE (see supplementary material 1). For this reason, we prefer to use KDE as the novelty scorer for our further experiments. The density score of KDE is inversely proportional to novelty and it may have negative values. We normalise the density scores such that they are proportional to novelty and non-negative values.1.

B. Generalization comparison for TL detector

In this section we show the influence of the novelty scores on CNN generalization ability. However, we do not have a ground truth generalization score for benchmarking. For this reason, we use various factors from the existing works that are known to control the network’s generalization ability, e.g., dropout rate, number of training iterations, batch size and learning rate. As the object-under-test we chose three CNN architectures, SSD and FRCNN with inception V2 backbone and SSD with mobilnet backbone. We follow the same evaluation method as in Section IV-A, except that we define the contamination samples based on the novelty and not TL colors. After scoring each TL object with a novelty score using KDE, we bin the test data into high, medium and low

1 Supplementary material: https://figshare.com/s/2613fa8fddae96895a6f

Fig. 4: Effect of various factors on the loss function
Batch size and network’s generalization ability are positively correlated [15]. From Figure 4c we infer that the SSD generalizes better on BSTLD dataset (c.f. Table I). However, in general we observed that the loss values of FRCNN detector are smaller in comparison to the SSD. Especially on high novel samples the average loss values of SSD was 0.59, whereas that of FRCNN was 0.46. Our \( \mathcal{G} \) score rewards this property to score FRCNN better than the SSD.

### C. Interpretation of novelty

In the previous sections, we use the word novelty to describe objects that are anomalous w.r.t. the training dataset. However, in practical applications the user needs to interpret novelty to further enrich the dataset or improve the CNN architecture. Therefore, in this section we aim to understand the latent dimensions because KDE scores the novelty based on these dimensions. Instead of visualizing all the \( d \)-dimensions, we used mutual information [14] to select dimensions that best classifies the samples into high and low novelty categories. Therefore, we analyse only the dimensions that strongly influence the novelty of objects. In Figure 6 and 7 we visualize the traversal (low to high values) of the influential dimensions in BSTLD and DriveU datasets respectively. We understand that the dimensions represent various human-interpretable properties of the image like brightness, color shade, inlay or the bulb size.

In Figure 8 and 9 we map the data samples and the traversals using parallel coordinates. Although we trained the detector for localization and not classification, we evaluate class-wise novelty as we found them to be more straightforward. However, the scoring was done over all colors at one shot and not class-wise. In Figure 8 we show the green and red TL samples of BSTLD dataset. We infer that dimension
controls the size of the traffic light bulb
(b) $z_2$ controls the background brightness
(c) $z_{19}$ controls the traffic light inlay

Fig. 6: Traversal of VAE latent dimensions trained on BSTLD dataset

(a) $z_{10}$ controls the white spot on the green traffic light
(b) $z_5$ controls the shades of yellow color light
(c) $z_{20}$ controls the shade of red color light
(d) $z_{23}$ controls the blurriness of the red yellow light

Fig. 7: Traversal of VAE latent dimensions trained on DriveU dataset

influences the novelty of green lights, i.e., smaller values of $z_9$ are scored as high novel samples. From our traversal study on $z_9$ in Figure 6a we interpret that it controls the size of the light bulb. That is, the $z_9$ is inversely proportional to the bulb size or the training data has more of smaller traffic lights.

This leads to the KDE assigning larger lights as more novel objects. The $z_2$ dimension is commonly influencing the novelty in green and red lights, from Figure 6b we understand that it controls the background brightness. The novelty scorer assigns the TLs with bright background as more novel. Similarly, for red TLs in Figure 8 we observe that smaller values of $z_{19}$ are more novel. The dimension $z_{19}$ controls the inlay, as we increase the value from left to right the image changes from a left facing arrow to red circled inlay (c.f. Figure 6c). From the perspective of human-interpretation, this means that the training dataset had fewer arrow inlays compared to the circle inlays.

Likewise, the interpretation study on the DriveU dataset for four different TL colors shows that novelty increases with increase in $z_{10}$ or $z_5$ (c.f. Figure 9). On contrary, the novelty of samples increase with the decrease of $z_{20}$ and $z_{23}$. From Figure 9a, we understand that $z_{10}$ controls the traffic light size and also the bright spot around it. These large TLs with such glaring white spots are deemed novel by the KDE. The $z_5$
dimension controls the shade of yellow, as we traversed to higher values we observed that the color was much darker, i.e., it tends to look more red in color, and it grew in size (c.f. Figure 9b). The $z_{20}$ dimension regulates the shade of red light color and $z_{23}$ controls the blurriness of the lights (c.f. Figure 9c and 9d respectively).

V. CONCLUSION AND FUTURE WORK

The fitness of the CNN depends on its ability to perform well on unseen data. However, existing works define unseen data as only the data not involved in the training. Such oversimplified definition of test data does not hold well for applications such as autonomous driving where we have streams of data from multiple sources. In this work we introduced the idea of scoring the generalization performance of CNN based on the sample’s novelty w.r.t. the training data. We demonstrated its usefulness in traffic light detection application for autonomous driving domain. Moreover, we experimentally compared various novelty scoring algorithm that fits for our application. In addition to our experimental evaluations on two datasets and CNN architectures, we use visualization methods to help users interpret the notion of novelty.

In this work, we evaluated the framework for TL applications which have standard shapes. However, evaluating the framework on non-standard shapes like pedestrian or vehicles is still an open challenge that we intend to pursue as future work.

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