Improving Prediction Confidence in Learning-Enabled Autonomous Systems*

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Abstract. Autonomous systems use extensively learning-enabled components such as deep neural networks (DNNs) for prediction and decision making. In this paper, we utilize a feedback loop between learning-enabled components used for classification and the sensors of an autonomous system in order to improve the confidence of the predictions. We design a classifier using Inductive Conformal Prediction (ICP) based on a triplet network architecture in order to learn representations that can be used to quantify the similarity between test and training examples. The method allows computing confident set predictions with an error rate predefined using a selected significance level. A feedback loop that queries the sensors for a new input is used to further refine the predictions and increase the classification accuracy. The method is computationally efficient, scalable to high-dimensional inputs, and can be executed in a feedback loop with the system in real-time. The approach is evaluated using a traffic sign recognition dataset and the results show that the error rate is reduced.

Keywords: Learning-enabled components · Prediction confidence · Conformal prediction.

1 Introduction

Autonomous systems are equipped with sensors to observe the environment and take control decisions. Such systems can benefit from methods that allow to improve prediction and decision making through a feedback loop that queries the sensor inputs when more information is needed [7]. Such a paradigm has been used in a variety of applications such as multimedia context assessment [2], aerial vehicle tracking [14], automatic target recognition [4], self-aware aerospace vehicles [1], and smart cities [8]. In particular, autonomous systems can utilize perception learning-enabled components (LECs) to observe the environment and make predictions used for decision making and control. LECs such as deep neural networks (DNNs) can generalize well on test data that come from the same

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distribution as the training data and their predictions can be trusted. However, during the system operation the input data may be different than the training data resulting to large prediction errors. An approach to address this challenge is to quantify the uncertainty of the prediction and query the sensors for additional inputs in order to improve the confidence of the prediction. The approach must be computationally efficient so it can be executed in real-time for closing the loop with the system.

Computing a confidence measure along with the model's predictions is essential in safety critical applications where we need to take into account the cost of errors and decide about the acceptable error rate. Neural networks for classification typically have a softmax layer to produce probability-like outputs. However, these probabilities cannot be used reliably as they tend to be too high, they are overconfident, even for inputs coming from the training distribution [9]. The softmax probabilities can be calibrated to be closer to the actual probabilities scaling them with factors computed from the training data. Different methods that have been proposed to compute scaling factors include temperature scaling [9], Platt scaling [13], and isotonic regression [16]. Although such methods can compute well-calibrated confidence values, it is not clear how they can be used for querying the sensors for additional inputs. Conformal prediction (CP) is another framework used to compute set predictions with well-calibrated error bounds [3]. The set predictions can be computed efficiently leveraging a calibration data set [11]. However, such approaches do not scale for high-dimensional inputs such as camera images. In our prior work, we have developed methods handling high-dimensional inputs using inductive conformal prediction (ICP) [5, 6].

This paper extends our prior work by designing a feedback loop between LECs used for classification and the sensors of an autonomous system in order to improve the confidence of the predictions. We design a classifier using ICP based on a triplet network architecture in order to learn representations that can be used to quantify the similarity between test and training examples. Given a significance level, the method allows computing confident set predictions. A feedback loop that queries the sensors for a new input is used to further refine the predictions and increase the classification accuracy. The method is computationally efficient, scalable to high-dimensional inputs, and can be executed in a feedback loop with the system in real-time. The approach is evaluated using a traffic sign recognition dataset and the results show that the error rate is reduced.

2 Triplet-based ICP

We consider an autonomous system that takes actions based on its state in the environment as shown in Figure 1. For example, a self-driving vehicle needs to take control actions based on the traffic signs it encounters. We design a classifier using ICP based on a triplet network architecture in order to learn representations that can be used to quantify the similarity between test and training examples. Given a significance level, the method allows computing confident set

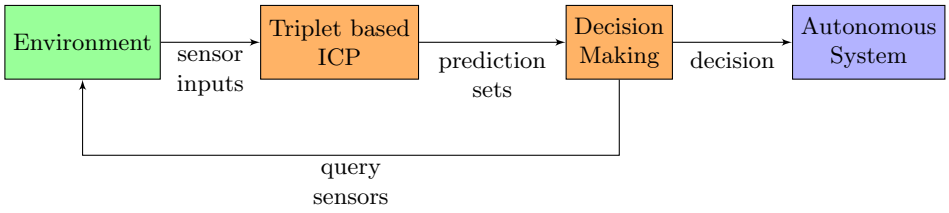


Fig. 1. Feedback loop between the decision-making process and sensing

predictions. A feedback loop that queries the sensors for a new input is used to further refine the predictions and increase the classification accuracy.

Triplet networks are DNN architectures trained to learn representations of the input data for distance learning [10]. The last layer of a triplet network computes a representation $Net(x)$ of the input x. For training, a triplet network is composed using three copies of the same neural network with shared parameters. It is trained on batches formed with triplets of data points. Each of these triplets has an anchor data point x, a positive data point x^+ that belong to the same class as x and a negative data point x^- of a different class. The objective is to maximize the distance between inputs of different classes $|Net(x)-Net(x^-)|$ and minimize the distance of inputs belonging to the same class $|Net(x)-Net(x^+)|$. To achieve this, training uses the loss function:

$$Loss(x, x^+, x^-) = max(|Net(x) - Net(x^+)| - |Net(x) - Net(x^-)| + \alpha, 0)$$

where α is the margin between positive and negative pairs.

The simplest way to form triplets is to randomly sample anchor data points from the training set and augment them by randomly selecting one training sample with the same label as the anchor and one sample with a different label. However, for many of these (x, x^+, x^-) triplets $|Net(x)-Net(x^-)| >> |Net(x)-Net(x^+)| + \alpha$, which provides very little information for distance learning and leads to slow training and poor performance. The training can be improved by carefully mining the training data [15]. For each training iteration, first, the anchor training samples are randomly selected. For each anchor, the hardest positive sample is chosen, that is a sample from the same class as the anchor that is located the furthest away from the anchor. Then, the triplets are formed by mining all the hard negative samples, that is the samples that satisfy $|Net(x) - Net(x^-)| < |Net(x) - Net(x^+)|$. When the training is completed, only one of the three identical DNN copies is used to map an input x to its embedding representation $Net(x)$.

Consider a training set $\{z_1, \ldots, z_l\}$, where each $z_i \in Z$ is a pair (x_i, y_i) with x_i the feature vector and y_i the label. We also consider a test input x_{l+1} which we wish to classify. The underlying assumption of ICP is that all examples (x_i, y_i), $i = 1, 2, \ldots$ are independent and identically distributed (IID) generated from the same but typically unknown probability distribution. For a chosen classification

significance level $\epsilon \in [0, 1]$, ICP generates a set of possible labels Γ^ϵ for the input x_{l+1} such that $P(y_{l+1} \notin \Gamma^\epsilon) < \epsilon$.

Central to the framework is the use of *nonconformity measures* (NCM), a metric that indicates how different an example z_{l+1} is from the examples of the training set $z_1, \ldots, z_l$. A NCM that can be computed efficiently in real-time is the *k-Nearest Neighbors* (k-NN) [12] defined in the embedding space generated by the triplet network. The k-NN NCM finds the k most similar examples in the training data and counts how many of those are labeled different than the candidate label y of a test input x. We denote $f : X \rightarrow V$ the mapping from the input space X to the embedding space V defined by the triplet's last layer. After the training of the triplet is complete, we compute and store the encodings $v_i = f(x_i)$ for the training data x_i. Given a test example x with encoding $v = f(x)$, we compute the k-nearest neighbors in V and store their labels in a multi-set Ω. The k-NN nonconformity of the test example x with a candidate label y is defined as:

$$\alpha(x, y) = |i \in \Omega : i \neq y|$$

For statistical significance testing, p-values are assigned based on the computed NCM scores using a calibration set of labeled data that are not used for training. The training set $(z_1 \ldots z_l)$ is split into two parts, the *proper training* set $(z_1 \ldots z_m)$ of size $m < l$ that is used for the training of the triplet network and the *calibration set* $(z_{m+1} \ldots z_l)$ of size $l - m$ that is used only for the computation of the p-values. The empirical p-value assigned to a possible label j of an input x is defined as the fraction of nonconformity scores of the calibration data that are equal or larger than the nonconformity score of a test input:

$$p_j(x) = \frac{|\{\alpha \in A : \alpha \geq \alpha(x, j)\}|}{|A|}.$$

The p-values are used to form the sets of candidate labels for a given significance level ϵ. The label j is added to Γ^ϵ if $p_j(x) > \epsilon$.

3 Feedback-loop for Querying the Sensors

Only the prediction sets Γ^ϵ that have exactly one candidate label can directly be used towards the final decision. When $|\Gamma^\epsilon| \neq 1$ the approach queries the sensors for a new input. Incorrect classifications are more likely to happen during the first time steps of the process as every sensor input offers new information that may lead to a more confident prediction. For example, in the traffic sign recognition task, it is more likely for an incorrect classification to happen when the sign is far away from the vehicle and the image has low resolution as shown in Figure 2. To avoid such incorrect classifications, in our method the final decision is made only after k consecutive identical predictions. The parameter k represents a trade-off between robustness and decision time, as larger k leads to additional delay but more confident decisions. Further, very low k values may lead to incorrect decisions while very large values may not allow a timely a decision.

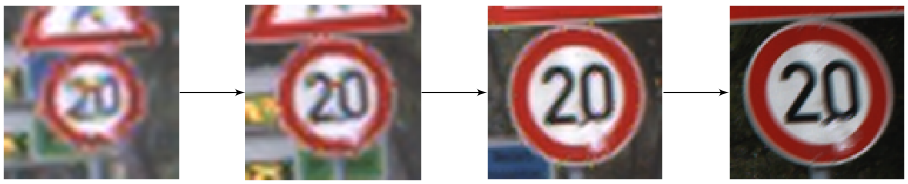


Fig. 2. Traffic sign over time (in frames)

The ICP framework produces well-calibrated prediction sets Γ^ϵ when inputs are IID. Depending on how small the chosen significance level is, Γ^ϵ may include a different number of candidate labels. The classification of an input requires $|\Gamma^\epsilon| = 1$. In our previous work [5,6], we use a labeled validation set to compute the minimum significance level ϵ to reduce the prediction sets with more than one candidate label. However, in dynamic systems, sensor measurements change over time. Each new input in a sequence is related to previous inputs and the inputs are not IID. In this case, even though the calculated significance level ϵ will not lead to $|\Gamma^\epsilon| > 1$, the actual error rate may not be bounded by ϵ.

The main idea is to utilize a feedback-loop in order to lower the error-rate. In order to reduce the incorrect predictions that may occur especially for low quality inputs, we require that $|\Gamma^\epsilon| = 1$ with identical single candidate label for k consecutive sensor measurements. When this condition is satisfied for an input sequence, the prediction can be used for decision making by the autonomous system.

4 Evaluation

Experimental Setup We apply the proposed method to the German Traffic Sign Recognition Benchmark (GTSRB). A vehicle uses an RGB camera to recognize the traffic signs that are present in its surroundings. The dataset consists of 43 classes of signs and provides videos with 30 frames as well as individual images. The data are collected in various light conditions and include different artifacts like motion blur. The image resolution depends on how far the sign is from the vehicle as shown in Figure 2. Since the input size depends on the distance between the vehicle and the sign, we convert all inputs to size 96x96x3. 10% of the available sequences is randomly sampled to form the sequence test set. 10% of the individual frames is randomly sampled to form another test set. All the remaining frames are shuffled and 80% of them are used for training and 20% are used for calibration and validation.

The triplet network is formed using three identical convolutional DNNs with shared parameters. We use a modified version of the VGG-16 architecture using only the first four blocks because of the reduced input size. A dense layer of 128 units is used to generate the embedding representation of the inputs. All the experiments run in a desktop computer equipped with and Intel(R) Core(TM)

i9-9900K CPU and 32 GB RAM and a Geforce RTX 2080 GPU with 8 GB memory.

Training Accuracy	Validation Accuracy	IID Testing	Sequence Testing
0.991	0.987	0.986	0.948

Table 1. Triplet-based classifier performance

Model Performance The triplet network can be used for classification of inputs using a k-Nearest Neighbors classifier in the embedding space. We first investigate how well the triplet network classifier is trained looking at the accuracy of the two test sets. One basic hypothesis of machine learning models is that the training and testing data sets should consist of IID samples. This is confirmed in Table 1 where the accuracy for the testing set of IID examples is similar to the training accuracy while the testing accuracy for the set that includes sequences is lower.

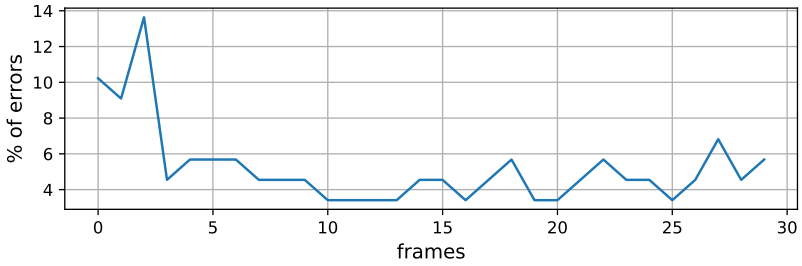


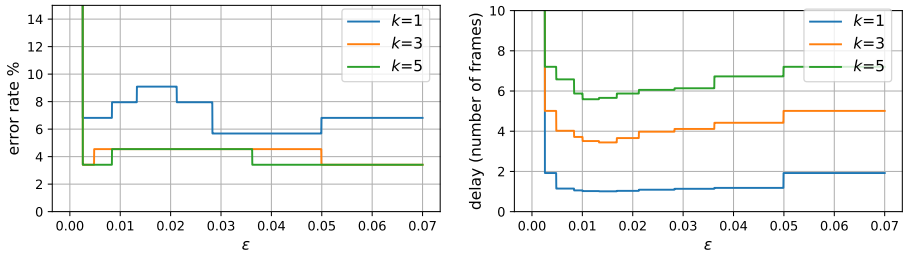
Fig. 3. Average error per frame for all the test sequences

In order to investigate which frames are responsible for the larger error-rate in the sequences we plot the average error-rate per frame for the 30 frames of all the test sequences in Figure 3. The early frames of each sequence tend to have more incorrect classifications as expected since the sign images have lower resolution.

	IID Test		Sequences Test	
ϵ	Errors	Multiples	Errors	Multiples
0.017	1.7%	0%	5.6%	0%

Table 2. Triplet-based ICP performance for individual frames

ICP Performance We apply ICP on single inputs to understand how the classifier performs without the feedback loop. The ICP is evaluated for both test sets in Table 2. An error corresponds to the case when the ground truth for a sensor



(a) (b)

Fig. 4. (a) Error-rate and (b) average number of frames until a decision.

input is not in the computed prediction set. We compute the smallest significance level ϵ that does not produce sets of multiple classes using the validation set. Similar to the point classifier, the ICP classifier produces well-calibrated predictions only for the IID test inputs.

Improving Prediction Accuracy We can improve the LEC classification performance using the feedback loop as described in Section 3. As we can see in Figure 3, the first frames of a sign tend to have more incorrect predictions as they have lower resolution and they lack details. Based on the feedback loop, the LEC uses a new input from the camera until the prediction remains the same for k consecutive frames. Experimenting with different values of k, Figure 4 shows that as k increases, the error-rate decreases for most of the ϵ values but the number of frames required to take a decision increases. When $\epsilon < 0.003$ the classifier enhanced with the feedback loop could not reach a decision. We also evaluate the efficiency of this classifier regarding to the real-time requirements. A decision for each new sensor query takes on average 1ms, which can be used with typical video frame rates. The memory required to apply the method consists of the memory used to store the representations of the proper training set and the nonconformity scores of the calibration data (45.9MB) and the memory used to store the triplet network (28.5MB) for a total of 74.4MB.

5 Conclusions

The ICP framework can be used to produce prediction sets that include the correct class with a given confidence. When the inputs to the system are sequential and not IID, applying ICP is not straightforward. Motivated by DDDAS, we design a feedback loop for handling sequential inputs by querying the sensors when a confident prediction cannot be made. The evaluation results demonstrate that when the inputs to the autonomous system are not IID, the error-rate cannot be bounded. However, the addition of the feedback loop can lower the error-rate by classifying a number of consecutive inputs until a confident decision can be

made. The running time and memory requirements indicate that this approach can be used in real-time applications.

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