# A Review on “Can Autonomous Vehicles Identify, Recover From, and Adapt to Distribution Shifts?”

Can Autonomous Vehicles Identify, Recover From, and Adapt to Distribution Shifts? **2.0***

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## ABSTRACT

Out-of-training-distribution (OOD) scenarios are a common challenge of learning agents at deployment, typically leading to random inferences and poorly-informed decisions. A potential method for detection of and adaptation to OOD scenes can mitigate their adverse effects. The paper “Can Autonomous Vehicles Identify, Recover From, and Adapt to Distribution Shifts?” (CAVIRADS) has proposed various methods that can partially answer questions such as: can autonomous vehicles identify, recover from, adapt to distribution shifts? However, there are some limitations to the methods proposed that prevents them from deployment. This paper highlights the downsides of various methods of the CAVIRADS paper through a critical review focusing on research relevance, applicability, logical approach, followed by proposing alternative methods which can outperform CAVIRADS’s methods. This paper also aims at proposing robust methods to mitigate data bias that eventually helps to decrease the number of human interventions, planning algorithm interventions through efficiently training on the data. The paper also attempts to answer some of the open questions of CAVIRADS’s. This paper also highlights the advantages of novel metrics and benchmarks proposed in the CAVIRADS paper over the existing evaluation methods.

## 1 Introduction

Autonomous driving (AD) vehicles don’t generalize well due to the ever-changing dynamics of the world which can’t be captured in a single training distribution. The CAVIRADS paper [1] has proposed multiple methods to tackle OOD scenarios where the model typically fails to generalize. However, the CAVIRADS methods along with other existing methods are prone to fail in evidentially quantifying uncertainty. The CAVIRADS has not proposed any method to mitigate the potential data bias on whose mitigation, the number of human interventions, planning algorithms interventions can be drastically decreased. The paper covers a quick critical review of the CAVIRADS paper highlighting the relevance of the research compared to earlier literature, the potential of the logical approach followed to recover from OOD cases and advantages of the proposed robust imitative planning (RIP) framework. The review also covers the limitations of the method proposed for quantifying epistemic uncertainty and introduces various methods to effectively mitigate data bias. The review also includes the advantages of the novel benchmark introduced called CARNOVEL over the other existing benchmarks. Further, the paper proposes the importance and advantages of evidential deep learning method with non-Bayesian neural networks [2] to effectively capture the evidence of a model’s prediction instead of just capturing the point estimate of likelihood by any other Bayesian neural networks through techniques such as ensemble of models [3] or Monte Carlo dropout [4]. The paper introduces a method to mitigate data bias [5] that often leads to poor performance on under-represented data. The paper also introduces a method to use fine-tuned neural style transfer algorithm [6] or swapping variational autoencoder approach [7] to augment data that helps to increase the model’s robustness on OOD scenes. Later, the paper highlights the importance of trying out and experimenting with other methods of aggregation to plan to recover from OOD scenes. In the last few sections, a critical review is added on introduced metrics and benchmarks to assess the robustness of the model on OOD scenes such as detection score, infraction score, recovery score, adaption score in the CARNOVEL benchmark.

## 2 Quick Review

The CAVIRADS’s methods for identifying, recovering from, adapting to distribution shifts have improved the performance of AD models in OOD scenes compared to the earlier approaches. However, the results are not very high as required for safe deployment. In this section, I review the methods proposed for various functionalities by giving the potential advantages and downsides. I also review the metrics adopted for assessing an AD model on OOD scenes in the novel benchmark introduced called the CARNOVEL. The CAVIRADS has used robust imitation learning to train the model on expert demonstration, used Bayesian neural networks to quantify uncertainty using ensemble or Monte Carlo dropout, and also used two aggregation operators. The two aggregation methods used are (a) one inspired by robust control [8] which encourages pessimism in the face of uncertainty and (b) another one is using Bayesian decision theory, which marginalizes the epistemic uncertainty to recover from OOD cases. The CAVIRADS also proposed an adaptive online feedback method to adapt to OOD scenes called AdaRIP (Adaptive Robust Imitative Planning) in cases of high uncertainties. Below I divide the algorithm into smaller parts and give a critical analysis covering all the aspects of the methods proposed.

**(a) Expert demonstrations for training:**

The CAVIRADS assumes access to a dataset of time-profiled expert trajectories (i.e., plans), y, paired with high-dimensional observations, x, of the corresponding scenes. The trajectories are drawn from the expert policy, y ~ πexpert(·|x).

CAVIRADS uses an autoregressive neural density estimator [9], as the imitative model, parametrized by learnable parameters θ. The likelihood of a plan y in context x to come from an expert (i.e., imitation prior) is given by the equation (1).

$$q(\mathbf{y}|\mathbf{x};\boldsymbol{\theta}) = \prod_{t=1}^{T} p(s_t|\mathbf{y}_{<t},\mathbf{x};\boldsymbol{\theta}) = \prod_{t=1}^{T} \mathcal{N}(s_t;\mu(\mathbf{y}_{<t},\mathbf{x};\boldsymbol{\theta}),\Sigma(\mathbf{y}_{<t},\mathbf{x};\boldsymbol{\theta})), \tag{1}$$

The method of using expert demonstrations to train the model to estimate the likelihood of a plan y in context x using Bayesian neural networks either by the method of ensembles or Monte Carlo dropout is robust and reliable when compared to the earlier uncertainty un-aware methods learning the likelihood of point estimate. However, the method of Bayesian neural networks to estimate the likelihood is compromised by the constraints that they are poorly applicable in real-time. Using Bayesian neural networks to estimate the likelihood of a plan y is a vanilla method that needs to be improved to deploy them in safety-critical domains such as AD. Some of the potential advantages of using Bayesian neural networks over traditional methods blindly aiming at point estimates also called deterministic models is that these probabilistic models can efficiently detect the uncertainty of the model's prediction through the disagreement of inferences between multiple ensembles or multiple samples of likelihood estimate. There are a few downsides to these probabilistic models though they perform better than previous methods, which are covered under (b) Uncertainty quantification.

**(b) Uncertainty Quantification**

The CAVIRADS used disagreement between the Bayesian neural network inferences to detect the epistemic uncertainty of the model's prediction. The CAVIRADS has used a probabilistic model to learn from expert demonstrations and detect the uncertainty in the model's prediction based on the variances of prediction distributions by ensemble models or using Monte Carlo dropout. The variance is calculated using equation (2).

$$u(\mathbf{y}) \triangleq \mathrm{Var}_{p(\boldsymbol{\theta}|\mathcal{D})}\left[\log q(\mathbf{y}|\mathbf{x};\boldsymbol{\theta})\right] \tag{2}$$

The probabilistic models used to detect the uncertainty of the model's prediction using the variance of likelihoods of the ensemble methods is a promising idea to efficiently tackle the uncertainty quantification when compared with previous methods. However, the same method doesn't guarantee safety and better performance in real-time due to the following constraints:

1. Time constraint: Probabilistic models require multiple models to be trained to use them to measure disagreement of inferences between those ensemble models that detect the uncertainty of model's prediction or multiple predictions have to be taken during the decision making of uncertainty in case of using Monte Carlo dropout where both the methods are not fit for deployment as they are time inefficient that prevents them from deploying into safety-critical-domains such as AD. The time inefficiency is common between both the methods either the ensemble of models or Monte Carlo dropout since both perform poorly in real-time.

2. Memory constraint: The method is memory inefficient as either multiple probabilistic models need to be trained or a single probabilistic model needs to be trained and used to predict the likelihood multiple times with Monte Carlo dropout to estimate the uncertainty in the model's predictions via variance. In the case of ensembles, the memory inefficiency is higher than that of Monte Carlo dropout as multiple trained ensemble models need to be stored to use these models with learned parameters in deployment.

3. The efficiency constraint: Both methods of probabilistic modelling, an ensemble of models or Monte Carlo dropout mentioned in CAVIRADS are better than the previous epistemic uncertainty un-aware methods. However, the efficiency and reliability are still the limitations as the real-time performance is below that required for deployment. These methods are prone to catastrophes for the reason that these quantify epistemic uncertainty using the likelihood estimations of Bayesian models but in real the epistemic uncertainty cannot be quantified using likelihood estimations for the fact that likelihood estimation of models is completely irrelevant with the confidence of the models in their predictions. The difference between likelihood estimates and confidence in the model's predictions is explained in the (c) Likelihood vs Confidence of the model on its prediction.

4. The calibration constraint: The Bayesian methods both ensemble of models or Monte Carlo dropout are inefficient in their prediction in real-time and also are sensitive to the priors. There may be chances for these models to be overconfident, since there are sensitive to their priors, especially in cases where it might lead to severe catastrophes.

5. The Compute Cost: The compute cost of using probabilistic models during training is huge as ensemble

of models need to be trained. The time constraint and memory constraint also lead to increased compute cost.

**(c) Likelihood vs Confidence of the model on its prediction**

The Bayesian neural networks detection the uncertainty of the model's predictions better than the previous uncertainty un-aware methods. However, these are prone to poor performance due to fact that these models rely on likelihood estimates of Bayesian models either ensemble of models or Monte Carlo dropout models to detect the epistemic uncertainty. The potential downsides as mentioned in the (b) Uncertainty Quantification are due to the misunderstanding between the words model's likelihood estimation vs the model's confidence in its prediction. There is a huge difference between the likelihood and confidence of the model which can be understood in figure1.

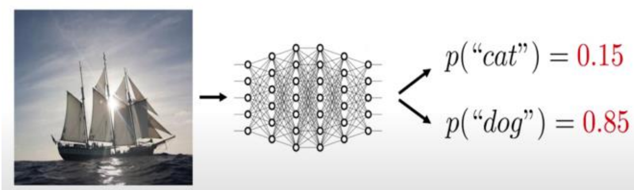


**Figure 1:Confidence vs Likelihood [10]**

As shown in figure1, the basic cat vs dog classifier predicts the likelihood of a boat/ship picture between the classes dog or cat as p("cat") is 0.15 and p("dog") is 0.85. Here the model's likelihood estimation of the picture is a dog class is 0.85 but the model's confidence in its prediction is not conveyed through its likelihood. The confidence of the model is the level of the model's confidence in its prediction/likelihood estimate which is closely related to epistemic uncertainty. Therefore, quantifying the model's (epistemic) uncertainty using the likelihood estimation of the model does not make much sense. A better method to quantify the model uncertainty is explained in section 3 via a method inspired by the paper "Deep Evidential Regression" [2].

**(d) Robust imitative planning (RIP), adaptive RIP(AdaRIP)**

The CAVIRADS has proposed a novel method to recover from OOD scenes called RIP that is efficient at drawing an inference to quantify the uncertainty using aggregation operators. In particular, the RIP has used 2 aggregation operators (a) one inspired by robust control [8] which encourages pessimism in the face of uncertainty by equation (3) and (b) another from Bayesian decision theory, which marginalizes the epistemic uncertainty by equation (4).

$$s_{\text{RIP-WCM}} \triangleq \arg\max_{\mathbf{y}} \min_{\boldsymbol{\theta} \in \operatorname{supp}\left(p(\boldsymbol{\theta}|\mathcal{D})\right)} \log q(\mathbf{y}|\mathbf{x};\boldsymbol{\theta}) \tag{3}$$

$$s_{\text{RIP-MA}} \triangleq \arg\max_{\mathbf{y}} \int p(\boldsymbol{\theta}|\mathcal{D}) \log q(\mathbf{y}|\mathbf{x};\boldsymbol{\theta}) \mathrm{d}\boldsymbol{\theta} \, . \tag{4}$$

Both of these methods have good potential to effectively plan a path to recover from OOD scenes. Both methods work well even in the deployment for the fact that they are fast and reliable to an extent. However, other methods can be used to draw an inference to recover from OOD scenes such as Conditional Value at Risk [11], [12] that employs quantiles or Mean-variance optimization [13], [14] can be also used, aiming to directly minimize the distribution shift metric. The need to try out these methods and check their performance on planning a path to recover from OOD scenes is very crucial, the reason being that each method has its pros and cons so building a novel method by integrating multiple methods to draw an inference to recover from OOD scenes increases the overall performance at efficiently planning a path and thereby decreasing the number of human interventions.

**(e) Novel metrics and benchmark**

The CAVIRADS has introduced novel metrics, benchmarks to effectively assess the model's robustness on especially OOD scenes. Various metrics and benchmarks introduced such as detection score, adaption score, recovery score of CARNOVEL benchmark are highly potential at assessing the models accurately on OOD scenes, unlike any other existing metrics or benchmarks. The evaluation metrics introduced are quite robust because they assess the models on all the required aspects including those which are missing in the current evaluation metrics like success rate or infractions per kilometre or recovery score, adaption score such as nuSences. There might be a need to add some more metrics to evaluate a model in cases other than OOD scenes but for assessing a model on typical OOD scenes, the proposed evaluation metrics and benchmark CARNOVEL are quite sufficient.

**2.1 Critical Comment on CAVIRADS paper**

The problem statement taken to propose a solution is quite a tough task, and also, the CAVIRADS paper proposed some of the very potential methods that partially answered the questions. Robust imitative planning (RIP) and AdaRIP framework proposed is a collection of methods to efficiently tackle the problem statement taken. The framework can be divided into 3 parts same as the problem statement i.e., can autonomous vehicles identify, recover from and adapt to OOD scenes. The 3 methods proposed to solve these three questions has improved performance over the previous methods such as conditioned imitation learning, learning by cheating which was poorly performing on OOD scenes. However, the methods for identifying the uncertainty of the model in OOD scenes is compromised due to some of the constraints as mentioned in section 2 (b) Uncertainty Quantification. The method for quantifying the uncertainty using likelihood doesn't guarantee its performance, the reason being, the uncertainty quantification is done through likelihood estimations which are misunderstood as the confidence of the model's predictions. Section 2 (c) clearly explains the difference between likelihood estimation vs confidence of model in its prediction along with highlighting the consequence of quantifying the epistemic uncertainty using the likelihood estimate. Another constraint as discussed earlier is that the probabilistic approaches either ensemble of models or Monte Carlo dropout are prone to be sensitive to prior use in likelihood estimation as it leads to over-confident catastrophes.

### 2.1.1 Strengths and Weaknesses

**Strengths:** In the methods, metrics and benchmark proposed, the method using aggregation operators to plan a path y to recover from OOD scenes is robust without any possible downsides in real-time deployment, however, alternative methods as discussed in section 2 need to be tried to conclude on the best approach. Various metrics and benchmark introduced for assessing the model specifically on OOD scenes performance is close to the ideal approach to assess any method specifically on OOD scenes performance so as of now it would be a good standard of evaluation.

**Weaknesses:** In the methods proposed, the method for training models i.e., Bayesian neural networks via ensemble of models or Monte Carlo dropout and method for epistemic uncertainty quantification perform poorly in real-time due to various constraints as discussed in section 2 (a), (b), (c), (d). The alternative promising methods inspired from work "deep evidential regression" and "de-biasing the data" [2], [5] would significantly improve the performance by enabling for real-time deployment and also answering all the potential constraints and limitations of corresponding methods proposed in CAVIRADS paper.

### 2.1.2 Relevance of the literature

The CAVIRADS paper has taken a potential problem to answer, the paper has partially answered the questions using some robust methods such as RIP for planning, vanilla methods for uncertainty quantification which need to be improved. The paper is the first of its kind that tried to answer the problem statement by introducing a novel RIP framework and evaluation standards. In previous works of literature, the aim of the research is confined to answering a narrow range of problems like focusing completely on either uncertainty quantification or new scene generalizability. Many of the previous literature has tried to generalize the model on OOD scenes with uncertainty un-aware methods which doesn't make much sense. Very few previous pieces of literature focused on building an uncertainty quantification method to generalize on the OOD scenes. Most of the literature which were focused on building an uncertainty aware method for generalizing models such as (Deep evidential regression [2]) have focused on a narrow set of problems such as only proposing methods to improve uncertainty quantification but CAVIRADS is the first of its kind to propose methods over a wider range of problem set by a robust imitative planning (RIP) framework integrating multiple methods to collectively answer the identification, recovering from and adapting to OOD scenes.

### 2.1.3 Factual shortcomings:

Though the CAVIRADS has proposed a framework to answer a wider range of problem statements, the proposed methods don't answer some of the limitations of a few vanilla approaches. Various constraints, limitations mentioned in sections 2, 3 of the CAVIRADS research proposals led to some of the open questions and incomplete details. Some of the open questions are:

1. Real-time epistemic uncertainty estimation
2. Real-time online planning
3. Resistance to catastrophes forgetting in the online adaption or AdaRIP [10]

These open questions are addressed in section 3. The open question 3 is related to the AdaRIP approach whose limitations are not highlighted in the CAVIRADS paper.

## 3 Future Research Scope and Promising Improvements

As discussed in section 2, the framework proposed is robust but has got some of the constraints, limitations from deploying in real-time. Especially the probabilistic models used for training on likelihood estimations y given x and uncertainty quantification using the likelihood estimates disagreement doesn't guarantee reliable performance. The metrics, benchmark proposed to seem to be standard evaluations of their kind. The methods used for planning also work well in real-time but experimenting with other approaches is crucial to decide the best possible approach. In this section, I propose the robust methods for (a) training the model on an evidential non-Bayesian neural network (a deterministic model) that learns to estimate the parameters of the distribution of distributions of likelihood estimations of either ensemble of models or Monte Carlo dropout that simultaneously learns both epistemic and aleatoric uncertainties instead of drawing inference on uncertainty form the likelihood estimates of probabilistic models, (b) a basic sampling method from the parameter estimates of the distribution of distributions to quantify the uncertainty accurately.

**(a) Deep evidential learning method [2]:** A method to learn the parameters of a prior distribution of distributions that efficiently captures both the epistemic uncertainty and aleatoric uncertainty directly without inferencing from any likelihood estimates. This method is also a likelihood estimation but estimating the parameters of distribution over distributions of likelihood estimates of various probabilistic models either using ensemble of models or Monte Carlo dropout, instead of just estimating the likelihood of y (path) distribution. Regular Bayesian or probabilistic methods learn to estimate the likelihood of y (paths) distribution and then estimates of y (path) are taken from an ensemble of models or Monte Carlo dropout to draw a final distribution over the likelihood distribution of probabilistic models to quantify uncertainty but evidential deterministic models learn the parameters of final distribution such that the distribution parameters convey the confidence and uncertainty in the model's predictions of a specific training dataset. The variance in the predicted parameters of final distribution is used to determine either aleatoric or epistemic uncertainty i.e. if the variance of variance parameter of estimated distribution parameters is huge then it corresponds to higher aleatoric uncertainty whereas if the variance of the mean parameter of estimated distribution parameters is huge than it corresponds to higher epistemic uncertainty. Figure 2 shows the method's approach of quantifying uncertainties.

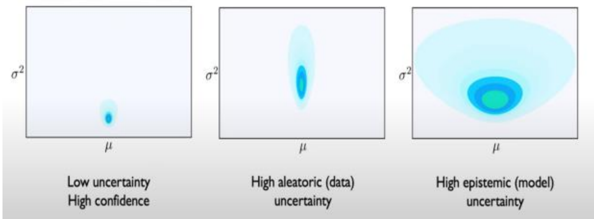


**Figure 2:The uncertainty quantification based on estimated distribution parameters**

The paper "deep evidential regression" [2] also proposes the best possible conjugate prior that works well in the practice as shown in figure 3:

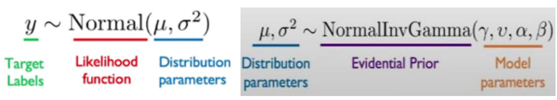


**Figure 3: Conjugate priors for Regression [2]**

The distribution parameters of a classification task belonging to Dirichlet distribution works well in practice where y belongs to categorical distribution.

(b) Basic sampling method to estimate the uncertainties: The method is to just sample values from the estimates of parameters to the distribution which gives the likelihood values of y (paths) along with the values to both epistemic and aleatoric uncertainties. Further, these values are used to apply aggregation operators to effectively plan a path to recover from the OOD scenes using RIP or other potential methods, and if the estimated values of uncertainties are beyond certain thresholds, then online adaption feedback either using AdaRIP or other aggregation methods to adapt online feedback in OOD scenes.

## 4 A method to mitigate data bias that decreases the number of human interventions.

**Motivation:** The potential bias typically exists which leads to an increased number of human or planning algorithm interventions. In data collection, potential bias creeps because the number of rare cases such as roundabouts or abnormal turns does exist in a small number that leads to less impact while training a model. Since the number of common examples such as straight roads exists high in number in the training data, the models tend to overfit these examples whereas learning no more than nothing from rare examples is crucial as they are sampled fewer times. The idea is that if the model trained better on both common examples and rare examples by increasing the samples of rare examples during training model can learn from rare examples as it does for common examples and decrease the number of human or planning algorithm interventions.

The idea is to use a VAE (variational autoencoder decoder) network [5] to learn equally from rare, low sampled examples by increasing the number of times the model learns from rare examples that mitigates data bias and also increases the performance on rare scenes with decreased number of human or planning algorithm interventions. The architecture of using VAE to mitigate data bias and learn effectively from under-represented data is shown in figure 4.

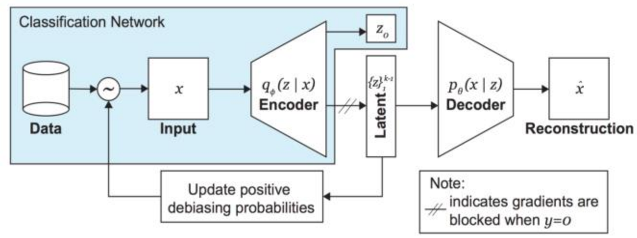


**Figure 4: VAE architecture to mitigate data bias [5], [15]**

## 5 A novel data augmentation method to improve model's real-time performance

**Motivation:** It is fact that some examples are rare in datasets due to the reason that there is a very low probability of these cases happening when compared with common scenarios like an aeroplane on the road. These potential data biases can be addressed by a method proposed in section 4. However, by the method proposed in section 4, the models can only resample rare examples and learn better from them as they do for common examples but they can't generalize to completely new demographics that are not at all existing in the training distribution, for example, an AD vehicle is trained in Indian roads where there is zero probability of experiencing snow roads than the model performs well on Indian or similar kinds of roads but can't generalize to snow places like London. In this section, I would propose a method that integrates methods proposed in the paper "Swapping Autoencoders for deep image manipulation" [7] to effectively use the method to manipulate the training distribution and create new training distribution resembling roads with snow that reduces the cost and effort of collecting completely new data from scratch. The method proposed in the paper "Swapping Autoencoders for deep image manipulation" [7] is very robust and can achieve something similar to that shown in figure 5 on images and videos. The same method can also be used for efficiently augmenting data to increase the training distribution. The method can also partially answer another challenging task of AD models such as domain adaption as it can manipulate the image or video data to new weather conditions or new environments as shown in figure 5.

**Figure 5: Results of Swapping VAE model on image manipulation [7]**

## 6 Future Tests

Due to the lack of data, I haven't done some of the important evaluations that are to be done to better assess the methods proposed in the CAVIRADS paper. Some of the important evaluations needed are as follows:

1. External validation of on various distributions of data on autonomous driving

2. Reproducing the results as stated in the CAVIRADS paper on the same datasets

## 7 Conclusion

In this paper, I have highlighted various limitations of methods in various stages of the RIP framework proposed in the CAVIRADS paper. This paper also gives a quick review and overview of the CAVIRADS paper with brief details on the methods involved in various stages of the framework. This paper also appreciates various metrics and benchmarks proposed that are well designed to assess a model's generalizability or performance especially on OOD scenes which are highly robust than any other existing benchmarks at assessing the model in the OOD. Finally, the paper proposes various promising deterministic methods to train model and quantify uncertainties effectively that addresses various constraints, limitations of probabilistic methods used in the CAVIRADS paper. Additionally, the paper also proposes some of the methods to be tried which can increase the performance by addressing data bias and by better data augmentation for improving the model's performance or generalizability on domain adaption.

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