SAfE: Self-Attention Based Unsupervised Road Safety Classification in Hazardous Environments

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Tech Report, Code, and Video at https://gamma.umd.edu/weatherSAfE

Abstract

We present a novel approach SAfE that can identify parts of an outdoor scene that are safe for driving, based on attention models. Our formulation is designed for hazardous weather conditions that can impair the visibility of human drivers as well as autonomous vehicles, increasing the risk of accidents. Our approach is unsupervised and uses domain adaptation, with entropy minimization and attention transfer discriminators, to leverage the large amounts of labeled data corresponding to clear weather conditions. Our attention transfer discriminator uses attention maps from the clear weather image to help the network learn relevant regions to attend to, on the images from the hazardous weather dataset. We conduct experiments on CityScapes simulated datasets depicting various weather conditions such as rain, fog and snow under different intensities, and additionally on Berkeley Deep Drive. Our result show that using attention models improves the standard unsupervised domain adaptation performance by 29.29%. Furthermore, we also compare with unsupervised domain adaptation methods and show an improvement of at least 12.02% (mIoU) over the state-of-the-art.

1. Introduction

Driving in adverse weather conditions is challenging not just for autonomous vehicles, but even for humans. Poor weather, such as heavy snow, rain, and fog can severely affect visibility, which is important for safe driving. Accident prevention in such poor weather conditions necessitates that the autonomous vehicle or human driver have a clear understanding of the scene. Accurate and robust computer vision algorithms can play a crucial role in providing driver assistance and making autonomous driving safer by semantically segmenting the suitable or driveable parts of the road, especially in hazardous conditions.

Recent advances in deep learning have been instrumental in fostering self-driving research and have improved performance have improved performance of semantic segmentation algorithms [3, 62, 44, 18]. These methods perform well on traffic data with good weather conditions by focusing uniformly on all the semantic classes (road, cars, persons, etc) and providing rich information about the context, layout and objects in the entire scene. However, in traffic with bad weather conditions, such approaches involving equal attention (the network treats all classes uniformly, in terms of learning feature representations) on all classes is unsuccessful as special attention is required with respect to specific semantic classes (in this case, 'roads'). Road segmentation requires the network to focus on safe, driveable areas of the road, and limit attention from regions that are not suitable for driving.

Modeling the attention of neural networks such that they may focus on specific labels has been studied extensively in the Natural Language Processing literature in problems such as vision-question answering, textual-visual matching [31, 48, 42, 27, 59] and also in recommendation systems [24, 56], and many of these techniques are being used in different computer vision applications such as textual-visual matching [21, 32] as well. Various forms of attention models such as self-attention, guided attention,
and co-attention have been proposed. In the self-attention model [48, 61], neural networks use their own feature representations to learn salient parts of an image. While self-attention has been used successfully to improve the accuracy of semantic segmentation for objects with well-defined boundaries [10], it would be useful to extend them to scenes that consists regions or objects without well defined shapes.

In addition, there is a compelling need for neural networks to learn in an unsupervised manner or leverage existing labeled data to generalize to new environments since data annotation, particularly for data corresponding to unfavourable weather conditions, is a laborious process. While there is an abundance of data for driving in clear weather and road scenes, models trained on the former do not generally transfer well to driving datasets captured in poor weather conditions due to the ‘domain gap’ problem [17, 16].

**Main contributions:** We present an approach to classify the safe, driveable regions of the road in unfavorable weather or hazardous driving conditions. Our approach is capable of explicitly detecting safe and unsafe non-road regions even in high intensities of rain and fog. The novel components of our approach include:

1. We propose the first use of self-attention in semantic segmentation for irregular objects, for example, roads or driving regions. The self-attention module takes advantage of the semantic relationships between regular-shapped and irregular objects (e.g. car (regular) drives on road (irregular), birds (regular) fly in the sky (irregular)) and uses these relationships to focus solely on roads. We explain the self-attention module in detail in section 4.1.

2. We develop novel strategies for unsupervised domain adaptive semantic segmentation with self-attention. Specifically, we propose a multi-level domain adaptation strategy with two domain discriminators— the ‘entropy minimization discriminator’ and the ‘attention transfer discriminator’, described further in section 4.2.

We have evaluated our approach extensively on snow [40], rain, and fog [14] under varying intensities by simulating images from the CityScapes and the Berkeley Deep Drive datasets. We show that the use of self-attention improves segmentation performance by up to 29.29%. The precision of our network is of the order of 85% − 95% in most of these adversities, indicating a low false positive rate, and thereby improved safety [1]. This demonstrates that our network is successful in terms of demarcating safe road regions. Finally, we compare with state-of-the-art unsupervised domain adaptation approaches [49] and outperform the next best method by at least 12.02%.

In the remainder of the paper, we discuss the related work in Section 2 and preliminaries in Section 3. We describe our main approach in Section 4. We present the experiments and results in Section 5 and conclude the paper in Section 6.

### 2. Related work

In this section, we review the relevant prior work in domain adaptation, and attention models in computer vision and NLP.

#### 2.1. Deep Learning for Driving in Hazardous Conditions

Classical computer vision techniques such as graph-cut segmentation, histogram-based segmentation have achieved reasonable success [22, 35, 2, 13] in segmenting safe roads. The advent of deep learning has bestowed models with increased abilities and have tremendously improved the performance of segmentation algorithms. Liu et al. [25] utilizes LIDAR data for unsupervised segmentation. Supervised/ Semi-supervised methods include [51] which uses depth information, and [23, 55] which perform supervised segmentation. One class of problems that deals with a class of problems similar to ours is the ‘drivable area’ [57] problem. The goal here is to segment out a lane for a vehicle under consideration, and also predict an alternate drivable lane. However, this class does not deal with segmenting safe/ unsafe drivable areas. Moreover, in the case of adverse weather conditions, lane segmentation may not be a viable option. The road agent may have to constantly maneuver at every point in time depending on the road situation.

#### 2.2. Attention Mechanism

Prior work in Natural Language Processing includes many forms of attention models such as recurrent attention [5, 53], self-attention[41, 43], modular attention[58], co-attention[59, 60, 27], etc for a multitude of tasks. Many of these ideas, specifically self-attention have also been attuned for semantic segmentation [20, 19, 10]. The focus of these papers is, however, to improve performance of multi-scale objects with fine-grained boundaries. These techniques are however not applicable to our problem where the goal is to focus on non-object categories (road).

#### 2.3. Domain Adaptation

A model trained on a source dataset $S$ may not work well on a target dataset $T$ due to the ‘domain-gap’ issue. On the other hand, annotating data for all domains is an arduous task. To this end, domain adaptation has emerged as a solution, wherein the goal is to enable a model to leverage source domain information to perform well on the target domain. Traditional domain adaptation [17, 16, 39, 50, 45, 6] methods have achieved remarkable success in adapting models from one domain to another. However, most of these models work on road images captured under clear weather and good road conditions. Driving in hazardous weather conditions like snow, fog and rain [47], and on poorly maintained roads (potholes, debris, puddles) [55] still remains a challenge. While there are techniques for object detection [54, 36] in rain and fog, these methods can’t segment out roads. In the context of segmentation, prior literature has seen the development of specific solutions [34, 29, 37, 8, 38, 33] for driving in rain and fog.
However, most of these methods use domain bridges, de-raining and dehazing priors, etc, which may be hard to obtain. In contrast, we propose a generic architecture that does not rely on specific details from each domain.

3. Preliminaries

In the section, we define the terminologies used in the paper and formalize the problem setup.

Definition 3.1. ‘Road’ and ‘Non-Road’ classes: Pixels of the image corresponding to areas that are safe to drive on, even under the prevailing adverse weather conditions, are classified as ‘road’. Regions of the image that are not suitable for driving are categorized as ‘non-road’ pixels.

At a high-level, our goal is to identify regions of the scene that are suitable for safe-driving, as well as those that are unsafe to drive on. We first formalize the problem of road segmentation, and then connect the segmentation task with the notion of road safety.

Problem 3.1. Road Segmentation: Given as input RGB images, \(I \in \mathbb{R}^{w \times h \times 3}\) and corresponding segmentation annotations, \(M \in \mathbb{R}^{w \times h}\) from a source domain \(S\) depicting clear weather conditions, and RGB images, \(\hat{I} \in \mathbb{R}^{w' \times h' \times 3}\) from a target domain \(T\) depicting hazardous weather conditions, our goal is to learn an output probability map \(P_{\text{out}} \in \mathbb{R}^{w' \times h' \times 3}\) for the target domain images which may be captured under rain, snow, fog or other hazardous weather conditions.

The first channel of \(P_{\text{out}}\) comprises of the probability of pixels belonging to the category ‘road’, while the second channel denotes the probability of pixels belonging to the category ‘non-road’. From \(P_{\text{out}}\), we can distinguish between safe and unsafe road areas using the following definition.

Definition 3.2. Road Safety: Given the predicted probability map \(P_{\text{out}}\), the unsafe regions of the road are indicated by the pixels classified as “non-road”.

The interpretation of this definition is that parts of the road that are covered by heavy snowfall or rainfall covering the road are deemed unsafe. Such parts that are covered by snow or water also more likely to be classified as “non-road”. Road safety classification thus proceeds in two steps. First, given an input image, solve Problem 3.1. Then using the output probability map \(P_{\text{out}}\), use Definition 3.2 to identify safe parts of the road.

Lastly, to measure the reliability of our approach to solve Problem 3.1, we use the precision value, which is an indicator of the number of false positives of a classification system. Blum et al. [1] studied the false positive rate as a metric for measuring the reliability of road segmentation methods in safety-critical applications such as autonomous driving. Therefore, we focus on this metric in our experiments.

3.1. Background on Self-Attention

Self-attention[48, 61] is a technique for transforming the original feature representation of an input image to one that amplifies a desired part of the image. This is done by learning the semantic relationships between various objects that are a part of the image. The modified feature representation, \(h\), is computed as,

\[
\hat{h} = \mathcal{T}^T \cdot h(I),
\]

where \(h(I)\) is an encoded feature representation of the input image \(I\) and \(\cdot\) denotes dot-product. The transformation is given by,

\[
\mathcal{T} = \text{softmax}(f(x)^T \odot g(x)),
\]

where \(x\) is the input feature map, \(f(\cdot), g(\cdot)\) are feature maps for the two objects \(o_1, o_2\) we wish to highlight, respectively\(^1\), and \(\odot\) represents mathematical scoring functions and typically include operations such as dot product, scaled dot product, matrix multiplication, and concatenation. Self-attention models generally use matrix multiplication. In this work, we want to highlight only those semantic relationships that involve the ‘road’ class. So for example, “car drives on road” or “pedestrians crossing the road”, and so on. In the first case, \(f(x)\) refers to the class, ‘car’, and \(g(x)\) refers to the class, ‘road’. Note the input to the self-attention module used to compute \(f(x), g(x), \text{and } dh(x)\) correspond to the same feature maps i.e. the self-attention module learns long range spatial dependencies within an image without any additional information.

The key idea behind self-attention is to transform \(h(I)\) in a way such that the features for the objects belonging to the desired semantic relationship are similar, and distinguishable from features of objects that do not belong to the semantic relationship. Using our earlier example, the feature representations for ‘car’ and ‘road’ would be similar to each other than, say, ‘road’ and ‘bird’.

We demonstrate self-attention used in road segmentation in Figure 2. In Figure 2a, we show an input image with two semantic relationships associated with the class, ‘road’. With self-attention by setting \(f(x) = \text{‘road’} \) and \(g(x) = \{\text{‘pedestrian’}, \text{‘car’}\}\) (constraining the ground truth in turn enables these feature maps to learn appropriate representations via backpropagation), we can capture the two semantic relationships captured car. (a) Rainy scene with pedestrians and (b) Semantic relationships captured using self-attention.

Figure 2: Self-Attention Example: (left) The input image consists of the semantic relationships, “pedestrians walk on the road” and “car drives on the road”. (right) We use self-attention to capture these semantic relationships related to the ‘road’ class. Capturing these road-related semantic relationships improves the performance of road segmentation.

\(^{1}\)\(f(\cdot), g(\cdot), h(\cdot)\) are referred to as key, query, and value, respectively, in the deep learning literature.
Figure 3: The Proposed SAfE Network. The architecture consists of a self-attention module to learn long-range semantic relationships in an image. Attention transfer and entropy minimization discriminators (pink blocks) help in unsupervised domain adaptation from the annotated clear weather images to the images captured under adverse weather conditions.

4. SAfE Algorithm

In this Section, we describe our approach for safe driving in adverse weather conditions. Our method is based on two key aspects:

1. A self-attention mechanism [61] that allows deep neural networks (DNNs) to explicitly distinguish between road and non-road pixels.
2. Using unsupervised domain adaptation to leverage the large number of images containing clear weather, which mitigates the disadvantage of limited number of training images corresponding to adverse weather conditions.

The method is illustrated in Figure 3. Our architecture consists of a road segmentation network (the generator network) and two domain discriminators. We begin by taking an input RGB image $\mathcal{I} \in \mathbb{R}^{w \times h \times 3}$, which is passed through an encoder to generate feature maps $F_{en}$. Next, we apply self-attention on these feature maps to obtain attention maps $F_{sa}$. These feature maps $F_{sa}$ are used to learn the final predictions $P_{out} \in \mathbb{R}^{w' \times h' \times 2}$. The generator and the discriminators are trained in a game-theoretic fashion [11]. We now describe each step in detail.

4.1. Road Segmentation with Self Attention

The goal of the road segmentation network is to generate an output probability map $P_{out} \in \mathbb{R}^{w' \times h' \times 2}$, that classifies pixels into road and non-road regions. The input consists of images $\mathcal{I}_s \in \mathbb{R}^{w \times h \times 3}$ belonging to a source domain $S$, ground-truth $\mathcal{Y} \in \mathbb{Z}^{w \times h}$, and a target image $\mathcal{I}_t \in \mathbb{R}^{w \times h \times 3}$ belonging to the target domain $T$. We begin by using an encoder (blue trapezoids in Figure 3) to learn a high-level representation of the image, $F_{en}$, which captures information such as context and spatial layout. The encoder is a Convolutional Neural Network (CNN) adapted from [3].

Self-attention [61, 48] seeks to capture long-range spatial dependencies across an image while being computationally efficient. This is crucial in our setup since objects in an autonomous driving scene are not entirely independent of each other. For instance, vehicles are generally found on the road, vegetation tends to be on the sides of the road, and traffic signs and poles don’t occupy too much ground area. These semantic relationships can determine regions of the scene that belong to road and non-road.

The feature maps generated by the encoder $F_{en}$ form the input to the self-attention module. In the first step of the self-attention module, the goal is encode the feature representation between objects. Since our focus is on road segmentation, one of the objects must be ‘road’. The other object may be a class where the pixels are spatially connected to the pixels of the road, for example, ‘car’ or ‘pedestrian’
(Figure 2). Using Equation 2, we compute a transformation $T$, where $f$ and $g$ are $1 \times 1$ convolutional kernels. The convolution layers corresponding to $f$ and $g$ help in generating feature representations for the objects between which we wish to find a relationship. $T$ is a matrix of size $C \times (H_{en} \times W_{en}) \times (H_{en} \times W_{en})$ that encapsulates the relationship between car pixels and road pixels, and car pixels and pedestrian pixels, where $C$ is the number of channels in $F_{en}$, and $H_{en} \times W_{en}$ correspond to the spatial dimensions of $F_{en}$. The next step is to apply this transformation to $h(F_{en})$ using Equation 1 to compute the self-attention feature map $F_{sa}$.

The output of the self-attention module $F_{sa}$ form the inputs to the decoder (blue trapezoids in Figure 3). We use a decoder with Atrous Spatial Pyramid Pooling (ASPP) [4, 3]. In ASPP, the input feature maps $F_{sa}$ are passed through convolution layers with different atrous rates (or dilations) in parallel (we use dilations of 6, 12, 28 [4] and 24, respectively), the results of which are concatenated and refined with a final convolution layer. This helps in enlarging the field of view of the filters to capture multi-scale context. A final application of softmax to normalize the outputs generates the final probability map $P_{out}$, of dimensions $2 \times H \times W$. The two channels correspond to probability maps denoting the probability of a pixel belonging to road or non-road categories, respectively.

4.2. Unsupervised Domain Adaptation with Self-Attention

We integrate self-attention with adversarial domain adaptation (shown as pink blocks in Figure 3) and leverage source domain information to learn optimal representations on the target domain. In unsupervised adversarial domain adaptation, a generator strives to produce outputs for source and target domain images such that the underlying domains of the two outputs are indistinguishable by the discriminator. If the discriminator succeeds in correctly identifying the sources, then the generators are updated through a cross-entropy loss function. The idea is to train the generator to produce outputs that resemble the target domain, and thereby, ‘adapt’ to it. We refer the reader to [46] for a detailed review on adversarial domain adaptation.

Generator: The self-attention road segmentation network described above serves as the generator. The source domain images are optimized separately first using the cross-entropy loss function,

$$ \mathcal{L}_{CE} = - \sum_{h,w,c \in C} y_{h,w,c} \log(P_{out}) $$

where $c$ denotes the object category (‘road’ and ‘non-road’), $h,w$ denote the height and width of the input images, and $P_{out} \in \mathbb{R}^{2 \times h \times w}$ is the output of the generator network applied to the source $S$.

Then, to align the source domain with target domain, we adopt the entropy minimization strategy put forth by [49, 52, 30]. In entropy minimization, we compute a weighed self-information map, $I_{SI}$, for both the source and target domains,

$$ I_{SI} = \frac{-P_{out} \log(P_{out})}{\log(C)} $$

where $C$ denotes the number of classes (in this case, 2). The dimensions of weighted self-information $I_{SI}$ is the same as the dimensions of the output probability map $P_{out}$. These weighted self-information maps are passed to the domain discriminators, and back-propagated through the generator, with another binary cross entropy loss term that aims to distinguish the domain that resulted in this output.

Discriminators: We apply a multi-level strategy [45, 49], operating at two levels of the network–at the output of the decoder (blue trapezoid in Figure 3) and at output of the self-attention module (golden blocks, Figure 3)–to align the feature maps of the source and the target domains using entropy minimization.

1. Output of Decoder: As the network produces low entropy on source domain due to the cross entropy loss function (Equation 3), entropy alignment between the source and target domains helps in indirectly minimizing the entropy of target domain images as well [49]. The inputs to this discriminator is the predicted weighted self-information map $I_{sa}$, from the source and target domain images, and the output of the discriminator is the probability that the weighted self-information $I_{sa}$ corresponds to the source or target domain.

2. Output of Self-Attention: While the entropy minimization of the final probability map learns feature representations that generalize well at the output level, the lack of alignment at the intermediate layers of the DNN results in structural inconsistency between the two domains. To address this issue, we apply discriminators on the self-attention feature maps, $F_{sa}$ to perform intermediate domain alignment between the source and target domains. Aligning self-attention feature maps enables the network to learn transferable attention feature maps, that helps the network in focusing on the relevant regions of the image in the target domain. Self-attention feature maps $F_{sa}$ obtained from the self-attention module are the inputs to the attention transfer discriminator, and the output of this discriminator is the probability that the attention maps $F_{sa}$ corresponds to the source/target domain.

The generator and discriminators are trained in an adversarial fashion [46] i.e. the weights of the generator are frozen while the discriminators are being trained (and vice-versa). The discriminators are trained using both source and target domain images and the training is stabilised using spectral normalization [28].

5. Experiments and Results

We will make all code publicly available. We defer the technical implementation details to the supplementary ma-
Evaluation protocol in the supplementary material. In addition, we show results on Berkeley Deep Drive [57] below. The datasets used, and the corresponding simulation strategies below.

1. Snow: We use Automold [40] to simulate snow images. In addition to altering the brightness of the image to resemble snow, we add crystals of snow at random locations (specified by pixels) on the road.

2. Rain and Fog: We use the rain and fog datasets simulated by Halder et al [14]. The simulation technique uses a particle rain (and fog) simulator to generate varying intensities of rain and fog, in addition to appropriately estimating the scene lighting and accurate photometric modeling to augment the images with a random amount of realistic rain and fog.

In addition, we show results on Berkeley Deep Drive [57] in the supplementary material.

5.2. Evaluation protocol

We evaluate our architecture on the following metrics.

1. Intersection over Union (IoU) and mean pixel wise accuracy (mAcc): These metrics are explained in detail in Long et al [26].

2. Precision, Recall and F1 score: Precision and Recall are indicators of the number of false positives and false negatives, respectively. Blum et al. [1] study the false positive rate as a metric for measuring the reliability of a road segmentation method in safety-critical applications such as autonomous driving. Therefore, we focus on the number of false positives in our experiments. The F1 score (F1) is a metric that seeks to balance precision and recall [12].

5.3. Results

We conduct experiments on three adverse weather conditions, presented in Table 1.

**Better Road Safety:** In many cases, we observe that the IoU and accuracy on non-road regions (4th and 7th columns) is higher than the corresponding numbers on road regions (3rd and 6th columns). We conjecture that this result arises due to the conservative nature of our approach in that it aims to minimize false positives. We validate our conjecture by measuring the precision (indicator of false positives) under all three weather conditions and note that we consistently maintain a high precision. Higher precision (or fewer false positives) have been studied in semantic segmentation as a metric of improved safety [15, 1].

**Varying Weather Intensity:** We experiment with varying intensities of rain and fog\(^2\). Higher intensity of rain indicates reduced visibility. With moderate rain (25 millimeters and 50 millimeters), we observe that our network is able to successfully segment both roads and non-roads with an accuracy of 97.06 and 96.13, respectively. Furthermore, high F1 scores of 0.96 and 0.94 demonstrate that there is a fine balance between precision and recall, and that the network is able to differentiate between safe and unsafe regions. 100 millimeters denotes heavy rain, wherein the overall accuracy of our system decreases by only 2.7%.

Our network is able to achieve comparable performance in terms of Precision and non-road accuracy scores, denoting that there is no compromise in safety. In the case of

\(^2\)We did not vary the intensity of snow as the snow data is manually simulated

| Intensity | mIoU (%) | IoU (Road) (%) | IoU (Non-road) (%) | mAcc (%) | Acc (Road) (%) | Acc (Non-Road) (%) | Precision (%) | Recall (%) | F1 score (%) |
|-----------|----------|----------------|-------------------|---------|----------------|-------------------|---------------|------------|-------------|
| I. Snow   |          |                |                   |         |                |                   |               |            |             |
| Random    | 87.12    | 82.81          | 91.43             | 93.93   | 88.78          | 96.46             | 0.92          | 0.89       | 0.91        |
| II. Rain  |          |                |                   |         |                |                   |               |            |             |
| 25 mm     | 93.57    | 91.40          | 95.74             | 97.06   | 94.86          | 98.15             | 0.96          | 0.95       | 0.96        |
| 50 mm     | 91.59    | 88.75          | 94.44             | 96.13   | 92.79          | 97.77             | 0.95          | 0.93       | 0.94        |
| 100 mm    | 85.96    | 81.00          | 90.92             | 93.45   | 84.97          | 97.60             | 0.95          | 0.85       | 0.90        |
| 200 mm    | 75.35    | 66.01          | 84.69             | 88.19   | 69.76          | 97.22             | 0.92          | 0.70       | 0.80        |
| III. Fog  |          |                |                   |         |                |                   |               |            |             |
| 30 m      | 81.52    | 75.97          | 87.08             | 90.82   | 88.32          | 92.05             | 0.84          | 0.88       | 0.86        |
| 75 m      | 84.62    | 79.7           | 89.54             | 92.58   | 88.62          | 94.52             | 0.8           | 0.89       | 0.89        |
| 150 m     | 87.08    | 82.69          | 91.46             | 93.93   | 88.19          | 96.75             | 0.93          | 0.88       | 0.91        |

Table 1: Main Results: Results of our proposed architecture under varying intensities of snow, rain and fog. Our network is able to identify road vs. non-road regions well under varying intensities of hazardous weather conditions. We are also able to reduce the number of false positives (or increased precision), a metric important in road safety applications [1].
Figure 4: **Qualitative results on fog and rain**: The heat maps (3rd column) show the region of safety. Yellow indicates safe regions, and purple indicates unsafe regions. Note the similarity with the contours drawn on the raw input image. The 2nd and 5th columns compare our model predictions with the ground-truth. The predicted entropy maps (4th column) show that our network is able to demarcate road and non-road regions clearly, with no uncertainty which is also reflected in the heat maps.

Figure 5: **Qualitative results on snow**: We show two inputs with snowy weather conditions. (b) and (e) are our model predictions and can be compared with the corresponding ground-truths (c) and (f). The purple and black regions indicate the ‘road’ and ‘non-road’ pixels, respectively.

Qualitative results: We show the road segmentation results of our model on rain and fog in Figure 4, and snow in Figure 5. The images have very low visibility, which makes driving very difficult. We observe that our network is able to predict road vs. non-road regions with a high accuracy. Specifically, we observe that our network is able to segment out regions such as persons, cars, trees as non-road regions under conditions which can even be troublesome for humans. In addition to showing the final predictions of the network, we also visualize the heat maps, which show extent of safety and entropy maps, which show that the network is able to clearly demarcate road and non-road regions with high probability.

Comparisons with prior work: While unsupervised domain adaptive road segmentation in adverse weather conditions hasn’t been explored in the past to the best of our knowledge, we compare our architecture against prior unsupervised domain adaptive semantic segmentation approaches under road segmentation settings. More specifically, we compare our architecture against the one of the current state-of-the-art methods ADVENT [49]. The results are shown in Table 2(a). ADVENT [49] combines multi-level domain adaptation [45] and entropy minimization. Our SAfE architecture outperforms ADVENT by 12.02%, in terms of mIoU score. We observe an improvement of 6.46%, and 8.33% in terms of mean accuracy and F1 score respectively. We attribute this improvement to the...
Table 2: Comparisons and Ablation Studies: We show that using self-attention improves unsupervised domain adaptive semantic segmentation by 29.29% (mIoU). Our method also improves the state-of-the-art domain adaptation method under similar conditions by 12.02% (mIoU).

Figure 6: Visualizing Self-Attention: Self-attention (3th column) captures the distinction between the road and non-road parts of the image. Note the similarity with the contours drawn on the raw input image. The 2nd and 4th columns compare our model predictions with the ground-truth.

Table 3: Analysis: We analyze our approach under different settings, which are discussed in Section 5.4.

6. Conclusion, limitations and future work

We present SAfE, a novel algorithm used for classifying driving scenes as safe vs. unsafe in unfavourable weather conditions. We define the notion of safe and unsafe regions by classifying the scene into road and non-road classes. SAfE uses self-attention to explicitly focus on roads, and leverages domain adaptation, with an attention transfer discriminator that helps target images learn relevant regions to attend to, in addition to an entropy minimization discriminator. We highlight the improvement in accuracy and reduction in false positives. Our approach has some limitations. While our network is successful in reducing the number of false positives (precision of the order of 85%−95%), its performance with respect to false negatives can be improved further, which is a direction for future work. Additionally, our model does not take into account driver behaviour, which can also contribute to road safety. Another aspect to explore is the presence of out-of-distribution objects on the road.
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Appendix A

A.1 Results on Berkeley Deep Drive

We show further results on adapting from supervised CityScapes [7] to unsupervised Berkeley Deep Drive (BDD) [57]. BDD consists of images captured around the US, and represents a mix of complex road scenarios such as rain, fog and snow under varying intensities. The results are presented in Table 4. We observe that the accuracy on the complex real-world dataset BDD is comparable against simulated adverse weather cityscapes datasets, which proves the efficacy of our network.

A.2 Network Architecture and Training

Generator self-attention road segmentation network
Encoder: For our encoder network, we use the first 3 blocks of DeepLab [3]. The spatial dimensions of the output feature maps are downsampled by a factor of 8, and has 1024 channels.

Decoder: We use an Atrous Spatial Pyramid Pooling (ASPP) [3] module in our decoder. Convolution layers with dilations 6, 12, 18, 24, are applied in parallel to the self-attention feature maps, the outputs of which are concatenated and refined to generate the final probability maps.

Hyperparameters: The segmentation loss for source domain images are constrained using the cross entropy loss, and the generator network is optimized using the stochastic gradient descent optimizer, with an initial learning rate of $5 \cdot 10^{-4}$, and decayed in a polynomial fashion at a moment of 0.9, and a decay of 0.0005.

Discriminators: The discriminators consist of 5 convolution layers, with kernel size 4. Each convolution operation is followed by spectral normalization [28], and Leaky ReLU. The discriminators are optimised with the Adam optimiser, set at an initial learning rate of $1 \cdot 10^{-4}$, and decayed in a polynomial fashion.

The generator and the discriminators are trained in an adversarial fashion [46].

A.3 Comparisons against Supervised Methods

We compare our unsupervised method against the current state of the art supervised method for road segmentation [9], which uses both road segmentation ground truth and depth information. The results are presented in Table 5. We notice that our unsupervised method, SAFE, which uses neither ground truth annotations nor depth information, is competitive to the current state of the art supervised method which uses both.

A.4 Qualitative Results

A.4.1 Rain, Fog and Snow

We show additional qualitative results of our method on rain, fog and snow datasets in Figure 7, Figure 8, and Figure 9 respectively. The images have very low visibility, which makes driving very difficult. We observe that our network is able to predict road vs. non-road regions with a high accuracy. Specifically, we observe that our network is able to segment out regions such as persons, cars, trees as non-road regions under conditions which can even be troublesome for humans. In addition to showing the final predictions of the network, we also visualize the heat maps, which show extent of safety and entropy maps, which show that the network is able to clearly demarcate road and non-road regions with high probability.

A.4.2 Visualizing Attention Maps

We visualize the attention maps (for the experiment on Rain - 100mm) in Figure 10, addition to the results presented in the paper. We observe that our attention-module is successful in attending to road and non-road regions.

| Method | mIoU (%) | mAcc (%) | Precision (%) | Recall (%) | F1 score (%) |
|--------|----------|----------|---------------|------------|--------------|
| SAFE (Ours) | 83.43 | 93.73 | 0.86 | 0.85 | 0.85 |

Table 4: Experiment III: Experiments on adapting from clear weather CityScapes [7] to Berkeley Deep Drive. Results of our method on adaptation from clear weather CityScapes to Berkeley Deep Drive which contains images captured under varying weather conditions. We observe that the accuracy on the complex real-world dataset BDD is comparable against simulated adverse weather cityscapes datasets, which proves the efficacy of our network.

| Method | mIoU (%) | mAcc (%) | Precision (%) | Recall (%) | F1 score (%) |
|--------|----------|----------|---------------|------------|--------------|
| SNE-RoadSeg [9] | 90.80 | 96.8 | 0.95 | 0.95 | 0.95 |
| SAFE (Ours) | 85.76 | 90.45 | 0.95 | 0.85 | 0.90 |

Table 5: Comparisons of our unsupervised method against supervised methods. Our unsupervised method is competitive against the current state-of-the-art supervised method which doesn’t uses not only segmentation ground truth, but also depth information.
Figure 7: **Qualitative results on rain:** The heat maps (3rd column) show the region of safety. Yellow indicates safe regions, and purple indicates unsafe regions. Note the similarity with the contours drawn on the raw input image. The 2nd and 5th columns compare our model predictions with the ground-truth. The predicted entropy maps (4th column) show that our network is able to demarcate road and non-road regions clearly, with no uncertainty which is also reflected in the heat maps.
Figure 8: **Qualitative results on fog**: The heat maps (3rd column) show the region of safety. Yellow indicates safe regions, and purple indicates unsafe regions. Note the similarity with the contours drawn on the raw input image. The 2nd and 5th columns compare our model predictions with the ground-truth. The predicted entropy maps (4th column) show that our network is able to demarcate road and non-road regions clearly, with no uncertainty which is also reflected in the heat maps.
Figure 9: **Qualitative results on snow:** The heat maps (3rd column) show the region of safety. Yellow indicates safe regions, and purple indicates unsafe regions. Note the similarity with the contours drawn on the raw input image. The 2nd and 5th columns compare our model predictions with the ground-truth. The predicted entropy maps (4th column) show that our network is able to demarcate road and non-road regions clearly, with no uncertainty which is also reflected in the heat maps.
Figure 10: **Visualizing Self-Attention:** Self-attention (3th column) captures the distinction between the road and non-road parts of the image. Note the similarity with the contours drawn on the raw input image. The 2nd and 4th columns compare our model predictions with the ground-truth.