Semantic Label Reduction Techniques for Autonomous Driving

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Abstract—Semantic segmentation maps can be used as input to models for maneuvering the controls of a car. However, not all labels may be necessary for making the control decision. One would expect that certain labels such as road lanes or sidewalks would be more critical in comparison with labels for vegetation or buildings which may not have a direct influence on the car’s driving decision. In this appendix, we evaluate and quantify how sensitive and important the different semantic labels are for controlling the car. Labels that do not influence the driving decision are remapped to other classes, thereby simplifying the task by reducing to only labels critical for driving of the vehicle.

I. INTRODUCTION

In the context of autonomous driving, semantic segmentation models are being widely used for the perception of the driving environment [1], [2] as well as for control of the ego-vehicle [3], [4]. Semantic maps offer several advantages over raw RGB data described below [4]:

- Figure 1 shows how two weather conditions have different RGB inputs but the same semantic pixel labels. Hence, if the correct semantic representation is used as input to predict the correct steering commands, the model does not need to learn for each and every weather condition.
- The semantic labels can precisely localize the pixels of important road landmarks such as traffic lights and signs. The status/information contained on these can then be read off to take appropriate planning and control decisions.
- A high proportion of the pixels have the same label as its neighbours. This redundancy can be utilized to reduce the dimensionality of the semantic scene. Hence, the number of parameters required to train the control module can then also be reduced.

![Figure 1](https://www.youtube.com/playlist?list=PLKWxSGEZd0AcvsC2N5trDhPbbeLdGLi3)

II. RELATED WORK

Semantic Sensitivity. The authors of [6] instituted a hierarchical structure for segregating the various semantic classes based on their relative importance by assigning them weights proportionate to their significance. Classes with differing importance were placed on the different levels of the hierarchy. A special "Importance Aware Loss" was introduced that stressed the need for correctly segmenting the more important semantic classes in comparison to less important ones.

III. GRAD-CAM

Gradient-weighted class activation maps (Grad-CAM) is a technique providing visual explanation on how a model classifies images [7], [8]. This is done by tracking the flow of gradients, to localize areas in the original input image that are important to the model for making the correct classification.
Our task of predicting the steering command is that of regression rather than classification. Nevertheless, by using the same Grad-CAM technique of tracking the flow of gradients, we can ascertain regions in the input RGB image and ultimately the corresponding semantic labels that are fundamental for the model to produce the correct steering command. We train a simple end-to-end model, whose architecture is described in Figure 2. The model has the following parameters: \( \text{channels} = 3, F_1 = 3, F_2 = 3, F_3 = 13, F_4 = 4 \).

| Layer Number | Layer Type       | Layer Input  | Layer Output |
|--------------|------------------|--------------|--------------|
| 1            | Convolution      | 1 x channels x 128 x 128 | 1 x F1 x 124 x 124 |
| 2            | Max pooling      | 1 x F1 x 124 x 124 | 1 x F1 x 62 x 62 |
| 3            | ReLU Activation  | 1 x F1 x 62 x 62 | 1 x F1 x 62 x 62 |
| 4            | Convolution      | 1 x F1 x 62 x 62 | 1 x F2 x 58 x 58 |
| 5            | Max pooling      | 1 x F2 x 58 x 58 | 1 x F2 x 29 x 29 |
| 6            | ReLU Activation  | 1 x F2 x 29 x 29 | 1 x F2 x 29 x 29 |
| 7            | Convolution      | 1 x F2 x 29 x 29 | 1 x F3 x 25 x 25 |
| 8            | Max pooling      | 1 x F3 x 25 x 25 | 1 x F3 x 12 x 12 |
| 9            | Flatten          | 1 x F3 x 12 x 12 | 1 x (F3 *144) |
| 10           | Fully Connected Layer | 1 x (F3 *144) | 1 x F4 |
| 11           | ReLU Activation  | 1 x F4       | 1 x F4       |
| 12           | Fully Connected Layer | 1 x F4       | 1 x 1 |

We track the backward gradient flow from layer 7 of the model right up till the input image, to hone in on regions that are of interest for driving. Figure 3 shows these regions overlaid on the original image as a heat map, where the color of the heat map corresponds to the intensity of relevance. Dark red color represents high importance, whereas light blue corresponds to regions of low relevance. It can be observed that the important regions for driving decision correspond to those with semantic labels of fences (row 1), road lines (row 2 and 4), vehicles (row 3), sidewalk boundary (row 5), and the road (row 6) itself. In row 2, the model is skipping shadows and only focusing on the visible road lines for decision making. Dark red represents regions of high importance, while light blue color represents portions of low relevance for the model for decision making.

IV. SEMANTIC LABEL REMOVAL TECHNIQUES

In this approach, we train an end-to-end model with the semantic labels as input. The model input has 13 channels, corresponding to the 13 semantic labels. The architecture of this model is described in Figure 2 with the following parameters, \( \text{channels} = 13, F_1 = 5, F_2 = 4, F_3 = 14, F_4 = 5 \).

Once this model is trained, we evaluate the sensitivity of each semantic label by feeding zeros to its corresponding channel and recording the change in error. The error is the mean squared error (MSE) between the steering angle predicted by the model and the ground truth. Zeroing out a channel effectively eliminates that label from the input. Removal of semantic labels which are critical towards making the driving decision would result in an increased error. Figure 4 shows the increase in error by removal of each of the semantic labels.

![Fig. 3. Some sample images and affiliated heat maps. While taking the appropriate steering decision, the model seems to be looking into regions for fences (row 1), road lines (row 2 and 4), vehicles (row 3), sidewalk boundary (row 5), and the road (row 6) itself. In row 2, the model is skipping shadows and only focusing on the visible road lines for decision making.](image)

![Fig. 4. Increase in error due to removal of each of the 13 semantic labels by zeroing out the channel corresponding to that label. The bar plot is arranged in descending order of error. The same order also provides an indication of the relative importance of that label towards making a driving decision.](image)
The bar plot is arranged in descending order of error and hence of label importance. From this method we observe that the error increases dramatically if we are to remove channels corresponding to sidewalks and road lines. Next are the roads and fence labels in order of importance. This method also seems to reaffirm our observation from the Grad-Cam approach in Section III that road lines and sidewalks are of utmost importance for the control model to execute the correct steering command.

V. LABEL REMAPPING

To predict the steering angle of the car, we train the model with a modular approach instead of an end-to-end learning approach, for reasons given in [4]. This approach is shown in Figure 5. The purpose of the perception module is to use the images captured by an RGB camera to extract semantic features of the scene. These extracted features are then fed to the control module which aims to produce the correct steering command.

Fig. 5. The perception module is trained as an encoder-decoder architecture, without any skip connections. The encoder sub-module first embeds the raw image into a lower dimensional latent vector. The decoder sub-module reconstructs the semantic scene from this latent vector. If the low-dimensional latent vector contains all the necessary information to reconstruct the semantic scene to a reasonable degree of accuracy, then we directly feed it as an input to the control module instead of the semantic labels. The architecture is same as that used by [4].

However, as demonstrated earlier, not all the semantic labels may be important for the driving strategy. Reconciling the conclusions from the 2 methods presented in Section III and Section IV we train a new perception module by remapping the semantic labels as described in Table I. Figure 6 shows some visualizations of the semantic maps resulting from this remapping.

![Figure 6](image)

**Fig. 6.** This figure shows 5 examples of how remapping influences the visual appearance of the semantic map. The 1st row contains the raw RGB image, the 2nd row are the corresponding semantic maps with all the 13 labels. The 3rd row are the semantics with labels remapped in accordance with Table I. Note, from the images in the 3rd row that those containing a pedestrian (5th column), vegetation (6th column) are remapped to the other class. Similarly, labels for poles are remapped to the fence class (1st and 2nd columns). remapped labels) shows that the remapped perception module produces a more stable segmentation reconstruction.

| Label       | Roads | Sidewalks | RoadLines | Fences | Vehicles | Pedestrian | Other |
|-------------|-------|-----------|-----------|--------|----------|------------|-------|
| Mapped to   | Flexible | Vegetation | Traffic Sign | Wall | Building | None | Other |
| Table I     |       |           |            |        |          |            |       |

Table I gives a comparison of the training, validation, and test performance of the 2 models trained on the normal and the remapped segmentation labels. It can be observed that the remapping of labels does not cause any degradation in performance. In fact, a comparison of video2 (perception trained with all labels) and video3 (perception trained with remapped labels) shows that the remapped perception module produces a more stable segmentation reconstruction. In the first row is the error for the control model whose perception module is trained with all labels, while the second row is for the perception module trained with the new remapped labels. The values in the table are the mean squared error (MSE) between the actual and the steering command predicted by the models represented in the order of $10^{-3}$.

**TABLE II**

| Segmentation Model | Training Error | Validation Error | Test Error |
|--------------------|----------------|------------------|------------|
| With all labels    | 5.68           | 9.39             | 9.15       |
| With remapped labels | 4.64           | 9.20             | 9.11       |

A. Discussion

The manner in which the remapping is to be done or how the sensitivity is calculated is arguable. For example, instead of just zeroing out the label for road lines it might have been worthwhile to see what would happen if we camouflage it into the road. This could be done by assigning the road line label to also be a road in the road channel. There could be a multitude of such possibilities to be considered, which may grow exponentially as we refine the segmentation map by increasing the number of semantic labels. Finding the important semantic labels is in itself a separate research topic. As explained in Section IV the authors of [4] have tried to address this problem in the context of autonomous driving.

VI. CONCLUSION

From the results of the experiments, we observed that training a perception module by remapping the less important semantic labels to other classes, did not lead to any degradation in model performance. The car was still able to be controlled under this approach. This has a positive repercussion in that the semantic classes to be labeled can be reduced thereby possibly curtailing the human effort.

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