Exploring Label Efficiency with Semi-Supervision and Self-Supervision Methods

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Abstract. Deep learning models demand a colossal volume of data for effective generalization and achieving superior performance, involving not only data collection but, more critically, the process of data annotation. This labor-intensive task of labeling each element within the data, be it vehicles, pedestrians, or other entities, requires a substantial workforce. Consequently, the amount of unlabeled data typically surpasses the amount of labeled data, and it becomes advantageous to find ways to leverage this untapped resource.

There are two major families of approaches that tackle this challenge by incorporating unlabeled data during the training process under the assumption that the prediction of a label should remain consistent despite transformations applied to the corresponding sample: Semi-Supervised and Self-Supervised Learning. For example, while not sure whether an image depicts a pedestrian or a cyclist, it is reasonably expected that a slight rotation of the image should not alter its classification. Semi-supervision methods require annotated data but can also utilize unlabeled data to improve training; specifically by using the model's predictions for these unlabeled data to generate pseudo-labels in cases where the model has high confidence. Self-supervision frameworks, on the other hand, rely solely on unlabeled data, employing pretext tasks to create artificial labels from the data itself, which help the model learn useful representations. For instance, the model might be trained to predict the rotation angle applied to an image, thereby learning to extract meaningful features. Approaches like Supervised Learning can later utilize the annotated data to fine-tune the model, helping it further refine its understanding and representation of the data, ultimately improving its performance on downstream tasks.

The study aims to make innovative contributions through an extensive comparative analysis of semi-supervision and self-supervision methods, with the primary objective of assessing their practical application and performance within the challenging domain of Autonomous Driving, adapting them for more particular tasks, such as semantic segmentation. As an additional objective, a practical software framework was developed, enabling other projects to benefit from these techniques.

The results indicate that these methods significantly improve label efficiency, with semi-supervised learning particularly adequate in scenarios with moderate amounts of labeled data and self-supervised learning in situations with large volumes of unlabeled data. In Autonomous Driving, these methods demonstrated marked improvements in semantic segmentation, showcasing robustness and adaptability. This study concludes that integrating these methods can substantially reduce the dependency on labeled data, paving the way for more efficient and scalable models.

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ACM Computing Classification System:

- Computing methodologies → Artificial intelligence → Computer vision
- Computing methodologies → Machine learning → Machine learning approaches → Neural networks
- Computing methodologies → Machine learning → Learning settings → Semi-supervised learning settings
- Computing methodologies → Machine learning → Learning paradigms → Unsupervised learning