U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

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

Francisco Gonçalves Cerqueira

Supervisor
Ricardo Pereira de Magalhães Cruz

January 26, 2024
Dissertation Planning
Master in Informatics and Computing Engineering

Table of Contents

Context

- Research and development efforts dedicated to equipping vehicles with perceptive systems capable of autonomous decision-making.
- Society of Automotive Engineers (SAE) classifies levels of automation from Level 0 to Level 5. [1]
- Progressing toward full automation, Artificial Intelligence and Deep Learning are crucial for refining algorithms in autonomous driving systems.
- Demands large quantities of training data.

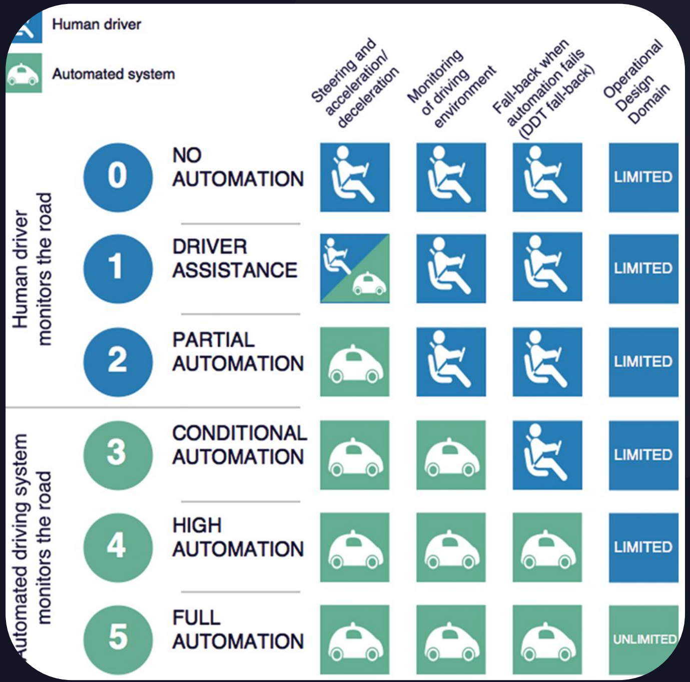

Fig. 1: SAE J3016 levels of driving automation. [2]

Motivation

Lower Speed

Higher Cost

Susceptible to Errors

Labor-intensive

Theia
Automated Perception Driving

Goals & Contributions

Annotation Dependency

Reduce the dependency of annotated data during the training. Can be done by using Semi-supervision or Self-supervision.

Comparative Study

Access and compare the used methodologies in the context of Autonomous Driving.

Software Package

Develop a software package including pertinent losses, simplifying the adaptation of these techniques to other domains.

Learning Paradigms

Supervised Learning

Model is trained on a labeled dataset, learning the relationship between input data and corresponding labels.

Tasks: Classification, Regression

Unsupervised Learning

Model is trained on an unlabeled dataset, seeking to discover inherent patterns, relationships, or structures within the data without explicit labels.

Tasks: Clustering, Dimensionality Reduction

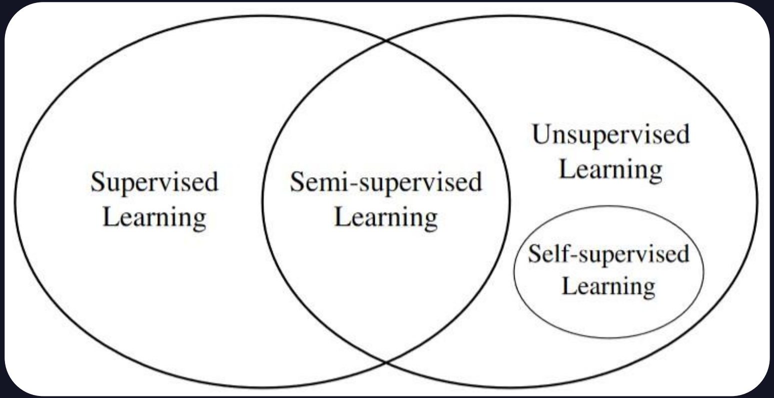

Fig. 2: Venn diagram representing the main learning paradigms.

Semi-supervised Learning

Overview

- Combination of SL and UL.
- Leverages labeled and unlabeled data at a single training instance.
- Comprises loss terms that leverage unlabeled data.
- Flexibility in regularizing the strength of those terms.
- Constrained to the task predetermined by the method.

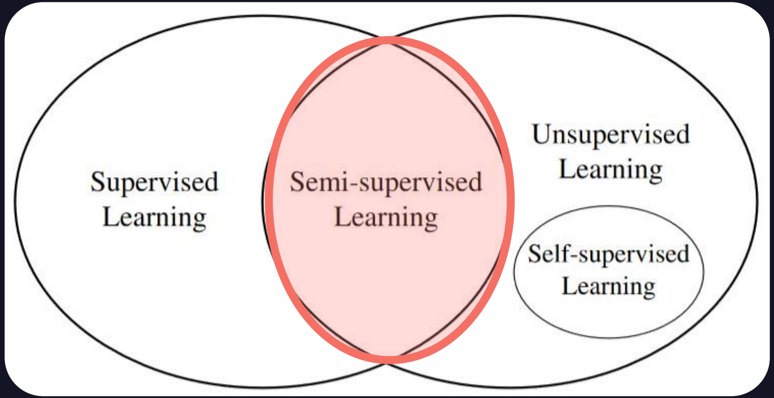

Fig. 3: Venn diagram representing the main learning paradigms with Semi-supervised Learning highlighted.

Categories

Consistency Regularization

Ensures model robustness through consistent predictions when presented with augmented versions of the same input. [3]

Entropy Minimization

Encourages low entropy/ high-confidence predictions on unlabeled data. Can be achieved with “temperature scaling”. [4]

Pseudo-labeling

Empowers the model to generate surrogate labels for unlabeled data by assigning “hard” labels. [5]

Π-Model [6]

Data Augmentation

Two distinct augmentations are performed for an input sample.

Unsupervised Term

The unsupervised term checks the consistency of both augmentations for every sample.

Supervised Term

If the sample belongs to the labeled set, a supervised term is also evaluated.

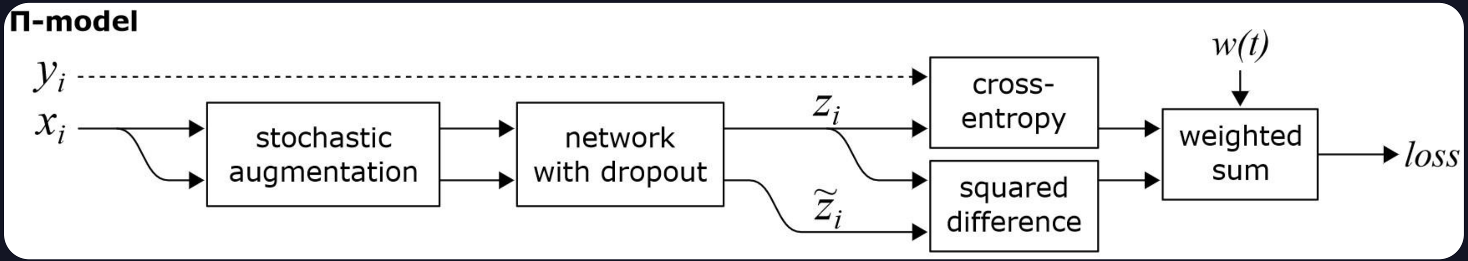

Fig. 4: Π-Model loss computation. [6]

Self-supervised Learning

Overview

- Subset of UL.
- Leverages only unlabeled data using a pretext task.
- Fine-tuning is performed later using other paradigms (e.g. SL).
- Easily adapted to any downstream task.

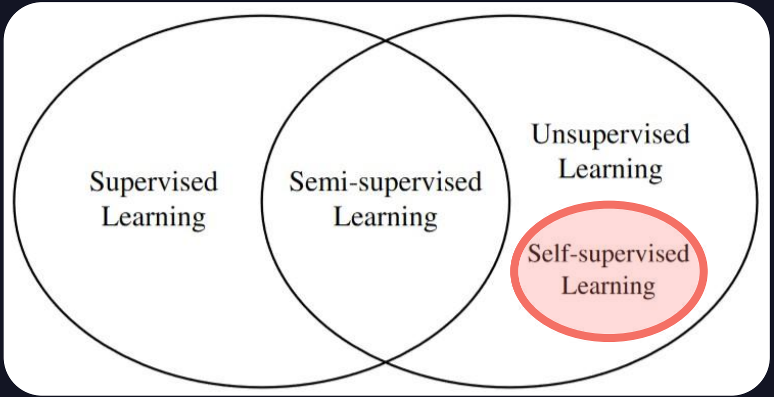

Fig. 5: Venn diagram representing the main learning paradigms with Self-supervised Learning highlighted.

Categories

Generative

Recreate realistic representations of unlabeled data by employing encoder-decoder architectures.

Requires substantial computational resources.

Contrastive

Contrast positive samples against a pool of negative or dissimilar samples.

Adversarial

Combines generative and contrastive elements.

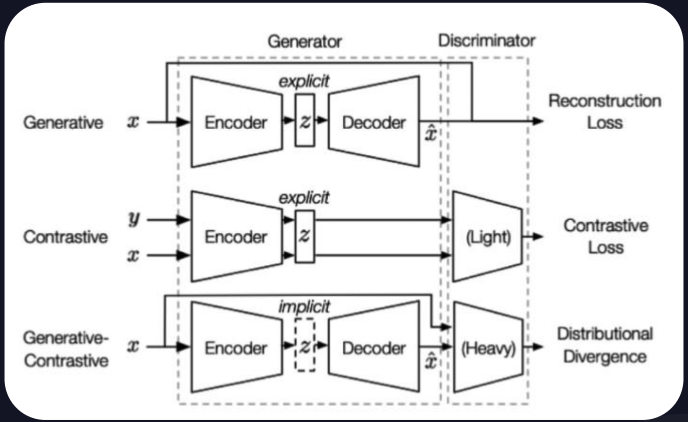

Fig. 6: Self-supervision categories. [7]

Proposed Solution

Techniques Selection

Select and implement Semi-supervision and Self-supervision methods.

Context Adaptation

Adapt the methods to Autonomous Driving context. Implies changing datasets, tasks, losses, and metrics.

Comparative Study

Evaluate the performance of these methods and compare them.

Software Package

Develop a software package including pertinent losses, simplifying the adaptation of these techniques to other domains.

Preliminary Work

Technique	Training Samples	Epochs	Training Speed (s/epoch)	Test Accuracy (%)
Supervised Learning	45000	200	7.6	94
Supervised Learning	4000	300	1.3	74
Π-Model [6]	45000 (4000 labeled)	300	11.9	80

Table 1: Preliminary experiments results.

Wide ResNet [8]

CIFAR-10 [9]

Work Plan

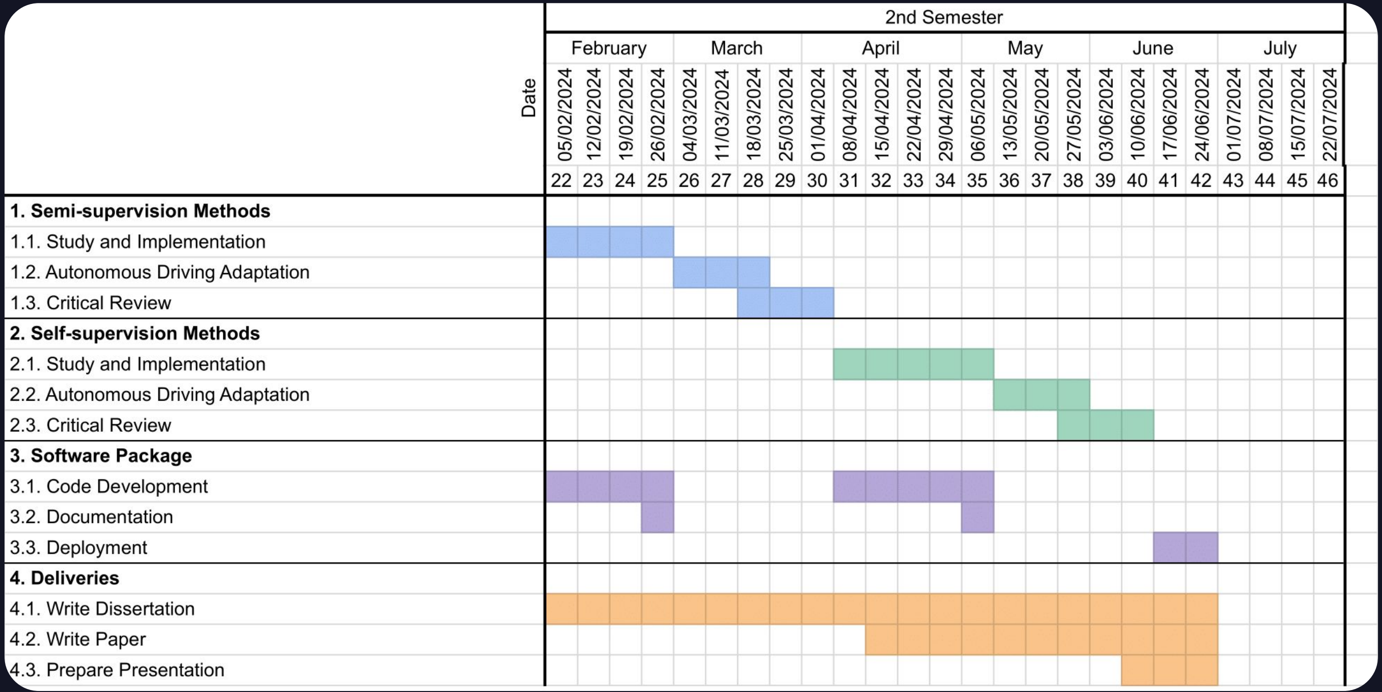

Fig. 7: Gantt chart illustrating the work plan.

Thank you!

Do you have any questions?

CREDITS: This presentation template was created by **Slidesgo**, and includes icons by **Flaticon**, and infographics & images by **Freepik**

References (1)

[1] Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. On-Road Automated Driving (ORAD) Committee, April 2021

[2] Alexandru Constantin Serban, Erik Poll, and Joost Visser. A standard driven software architecture for fully autonomous vehicles. In 2018 IEEE International Conference on Software Architecture Companion (ICSA-C), pages 120–127. IEEE, 2018

[3] Philip Bachman, Ouais Alsharif, and Doina Precup. Learning with Pseudo-Ensembles. Advances in neural information processing systems, 27, 2014

[4] Yves Grandvalet and Yoshua Bengio. Semi-supervised Learning by Entropy Minimization. Advances in neural information processing systems, 17, 2004.

[5] Geoffrey J McLachlan. Iterative Reclassification Procedure for Constructing an Asymptotically Optimal Rule of Allocation in Discriminant Analysis. Journal of the American Statistical Association, 70(350):365–369, 1975

References (2)

[6] Samuli Laine and Timo Aila. Temporal Ensembling for Semi-Supervised Learning. In International Conference on Learning Representations, 2017.

[7] Xiao Liu, Fanjin Zhang, Zhenyu Hou, Li Mian, Zhaoyu Wang, Jing Zhang, and Jie Tang. Self-Supervised Learning: Generative or Contrastive. IEEE transactions on knowledge and data engineering, 35(1):857–876, 2021.

[8] Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. arXiv preprint arXiv:1605.07146, 2016.

[9] Alex Krizhevsky, Geoffrey Hinton, et al. Learning Multiple Layers of Features from Tiny Images. 2009.