



U3 MACHINE LEARNING ALGORITHMS

U3.E3 SEMI-SUPERVISED MODELS

Machine Learning Engineer

January 2021, Version 1

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The student is able to

MLE.U3.E3.PC1	Define and understand semi-supervised learning.
MLE.U3.E3.PC2	Know some of the most commonly used algorithms in semi-supervised learning.
MLE.U3.E3.PC3	Know the domain application of semi-supervised models.

Is it possible to improve the quality of learning by combining labeled and unlabeled data?

- ➡ There is usually a lot more unlabeled data available than labeled.
- ➡ Semi-Supervised Learning (SSL) is a mixture between supervised and unsupervised approaches.
- ➡ In addition to unlabeled data, the algorithm is provided with some supervision information – but not necessarily for all examples.

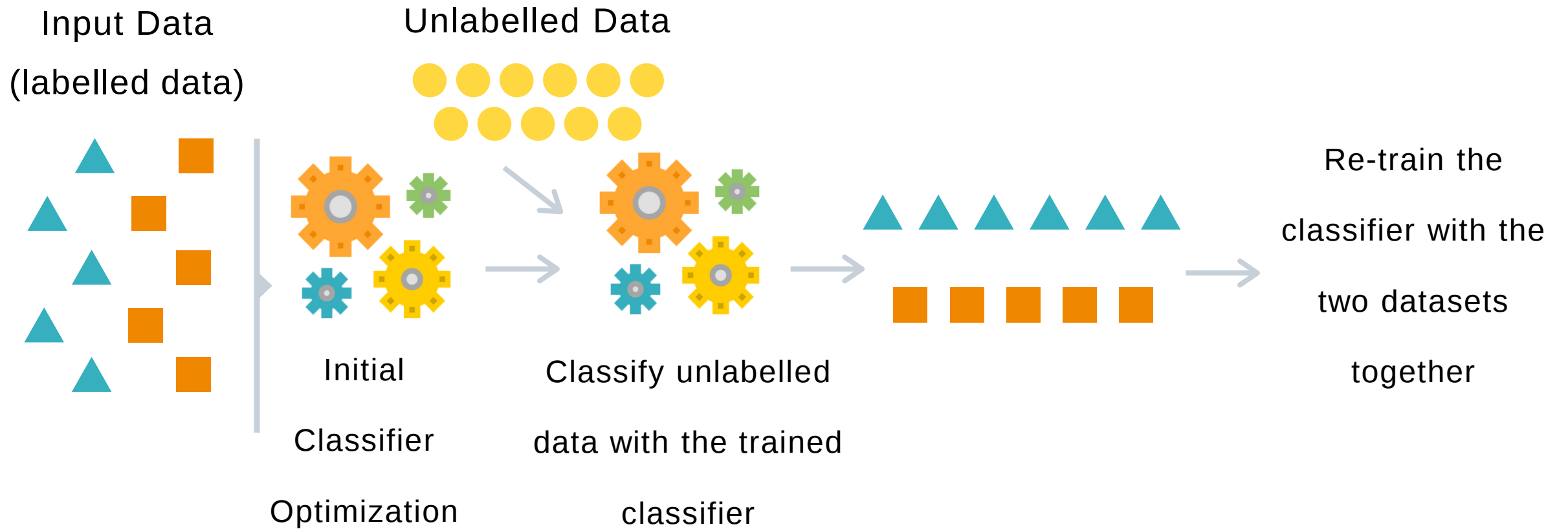


As the name suggests, SSL is halfway between supervised and unsupervised learning.

The dataset consists of a combination of labelled and unlabelled data

First, similar data is grouped using an unsupervised learning algorithm and only then the supervised learning algorithms are applied

It can refer to either transductive or inductive learning



➡ *Labeled vs. Unlabeled Data*

0 1 2 3 4 5 6 7 8 9

"0" "1" "2" "3" "4" "5" "6" "7" "8" "9"



➡ Human Expert / Special Equipment ➡

"dog" "cat" "dog"

Unlabeled data, X_i

Labeled data, Y_i

Cheap and Abundant

Expensive and Scarce

Feature Space X

Label Space Y

GOAL: Construct a predictor f to minimize $R(f) \equiv \mathbb{E}_{XY}[loss(Y, f(X))]$

An optimal predictor (Bayes Rule) depends on unknown P_{XY} . So, instead *learn* a good prediction rule from training data $\{(X_i, Y_i)\}_{i=1}^n$ iid $P_{XY}(\text{unknown})$

Training Data

$\{(X_i, Y_i)\}_{i=1}^n$

labeled



Learning Algorithm



Prediction Rule

$\hat{f}_n$

Training Data

$$\{(X_i, Y_i)\}_{i=1}^n$$

$$\{X_i\}_{i=1}^m$$



Learning Algorithm



Prediction Rule

$$\hat{f}_{n,m}$$

Supervised Learning

Labeled Data $\{(X_i, Y_i)\}_{i=1}^n$



X_i

“dog”

Y_i

Semi-Supervised Learning

Labeled Data $\{(X_i, Y_i)\}_{i=1}^n$ and Unlabeled Data $\{X_i\}_{i=1}^m$

$$m \gg n$$

Goal: Learn a better prediction rule than based on labeled data alone.

➡ COGNITIVE SCIENCE

Computational modal of how humans learn from labeled and unlabeled data:

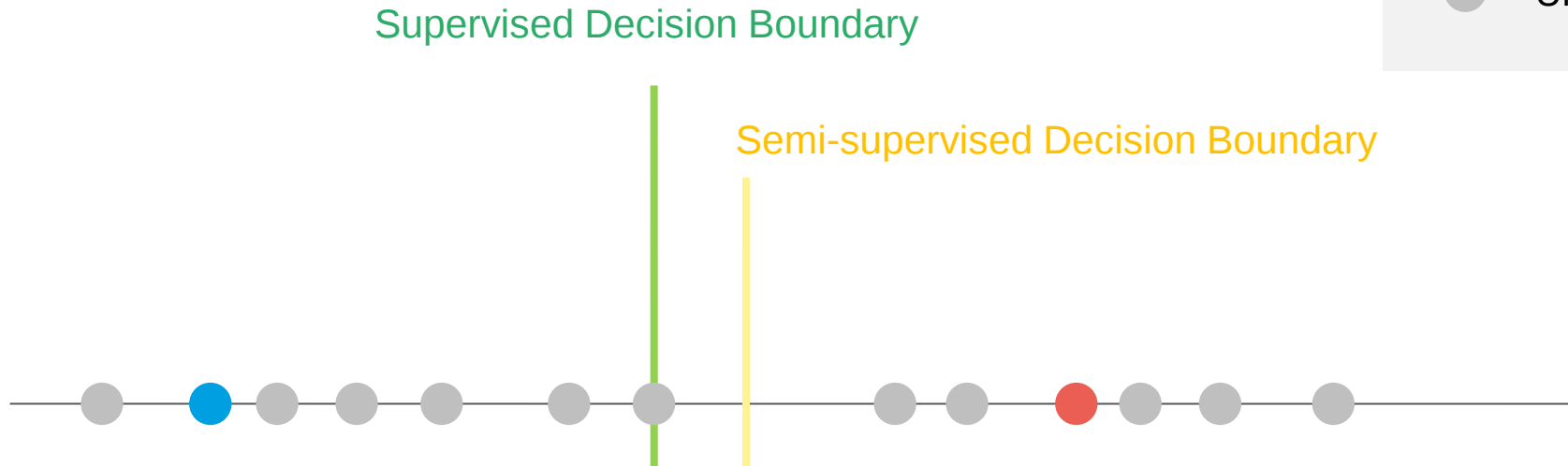
- Concept learning in children: x =animal, y =concept (e.g. cat)
- Dad/Mum points to an animal and says “this is a cat”
- Children also observe animals by themselves



CAN UNLABELED DATA HELP?

“Similar” data points have “similar” labels

- Positive labeled data
- Negative labeled data
- Unlabeled data



Assume each class is a coherent group (e.g. Gaussian)



Then, unlabeled data can help identify the boundary more accurately

➡ WHY SHOULD WE USE SSL?

- Labeling data is usually expensive, specially when a significant number of cases are being addressed;

I have a good idea, but I can't afford to label lots of data!

- Even when labeled data are available in significant amounts, it is useful to use more data to introduce as much variability as possible in the studies carried out;

I have lots of labeled data, but I have even more unlabeled data available!

- Domain adaptation.

I have labeled data from a domain, but I want a model for a different domain!

➡ SSL ALGORITHMS

- Self-Training
- Generative models
- Mixture models
- Graph-based models
- Co-Training
- Semi-supervised SVM or Transductive Support Vector Machine (TSVM)
- ...

Transduction refers to reasoning from observed specific (training) cases to specific (test) cases. In contrast, **induction** means reasoning from observed training cases to general rules, which are then applied to the test cases.

Hence, **Inductive Learning** can be seen as the same as traditional supervised learning, in which a machine learning model is built and trained based on the labeled training data. Then, the trained machine learning model is used to predict the labels of the testing data, which the model has never seen before.

Transductive Learning techniques, on the contrary, observe all the data, both the training and testing datasets, beforehand. Here the model learns from the already observed training dataset and then predicts the labels of the testing dataset. Although the labels of the testing datasets are unknown, the model can make use of the patterns and additional information present in these data during the learning process.

- ✓ Can only predict the points encountered in the test set based on the observed training set.
- ✓ Does not build a predictive model. If a new unlabeled data point is added to the test data, we will have to re-run the algorithm from the beginning.
- ✓ More computational cost

- ✓ Can predict any point in the space of points beyond the unlabeled points.
- ✓ Builds a predictive model. If a new unlabeled data point is added to the test data, we can use the initially built model.
- ✓ Less computational cost

- Most approaches make strong model assumptions (guesses).
- Some commonly used assumptions:
 - Clusters of data are from the same class
 - Data can be represented as a mixture of parameterized distributions
 - Decision boundaries should go through non-dense areas of the data
 - Model should be as simple as possible

- Semi-Supervised Learning is a mixture between supervised and unsupervised approaches.
- In SSL, the dataset consists of a combination of labeled and unlabeled data. The similar data is grouped using unsupervised learning algorithms and then, supervised learning algorithms are applied.
- SSL can be either transductive or inductive learning. The main difference between these types of SSL is the fact that transductive learning uses the test data to train the model whereas inductive learning only uses the training data and then applies the model to predict unseen instances.



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This Training Material has been certified according to the rules of **ECQA – European Certification and Qualification Association**.

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Thank you for your attention

DRIVES project is project under [The Blueprint for Sectoral Cooperation on Skills in Automotive Sector](#), as part of New Skills Agenda.

The aim of the Blueprint is **to support an overall sectoral strategy and to develop concrete actions to address short and medium term skills needs.**

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