Demystifying: Machine Learning
Part 1

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Schedule	Sunday, 28 July
Part One: Introduction to Machine Learning	
Introduction to machine learning	09:00 - 09:45
Applying supervised learning for performance prediction and estimation	10:00 - 10:45
Applying semi-supervised and unsupervised learning for anomaly detection	11:00 - 11:45
Part Two: Applications of Machine Learning	
Introduction to convolutional neural networks (CNNs)	14:00 - 14:45
Applying a CNN for the identification of Young's slit separation directly from a diffraction pattern.	15:00 - 17:00

Agenda

- Introduction to machine learning
  - Vocabulary
  - Supervised, semi-supervised, and unsupervised learning
  - Demystifying applications of machine learning
  - Setting up Google Colab
  - Data analysis
  - Use cases
  - General data exploration and preparation
- Applying supervised learning for performance prediction and estimation
- Applying semi-supervised and unsupervised learning for anomaly detection

Vocabulary

Features

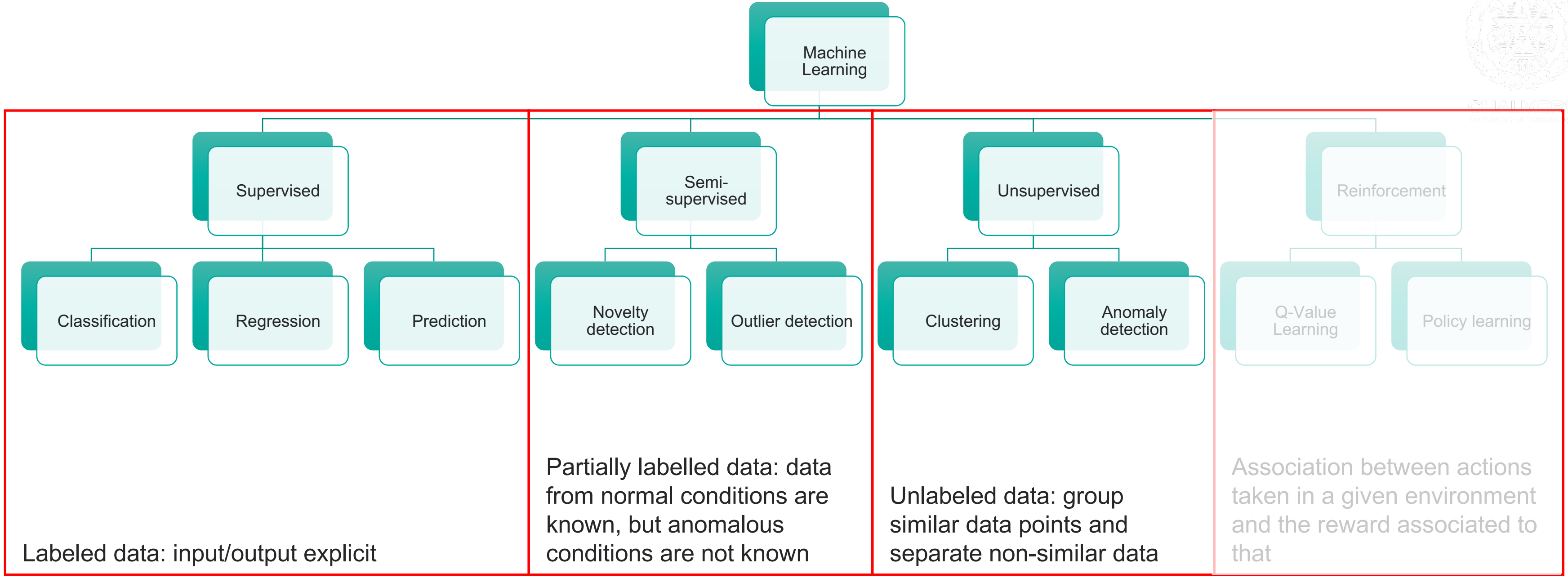
Label

size	edge	color
small	dotted	green
big	striped	yellow
medium	normal	green

Observations / Samples

https://medium.com/@ranjeetjangra/features-and-labels-in-ai-bb66b78a93b8

Machine learning methods



Supervised learning

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- A representative data set is collected, labeled and used to train the algorithm
- Complete information regarding what should be learned is available
- Fine-granular diagnostic info can be reported to the network management system
  - Presence of anomaly/attack, its type, intensity, or location

But:

- Anomalies/threats evolve and new ones emerge
- A representative data set is not always available
- Data labelling can be infeasible or too costly
- Complete information regarding what should be learned (e.g., normal/abnormal conditions) is not always available

Semi-supervised and unsupervised learning techniques can help!

M. Furdek, et al., "Machine learning for optical network security monitoring: A practical perspective," IEEE/Optica JLT, April 2020.

Unsupervised vs. semi-supervised learning

Requirements:
- **No prior knowledge of anomalies**
- **Only anomaly presence can be reported**

Semi-supervised learning

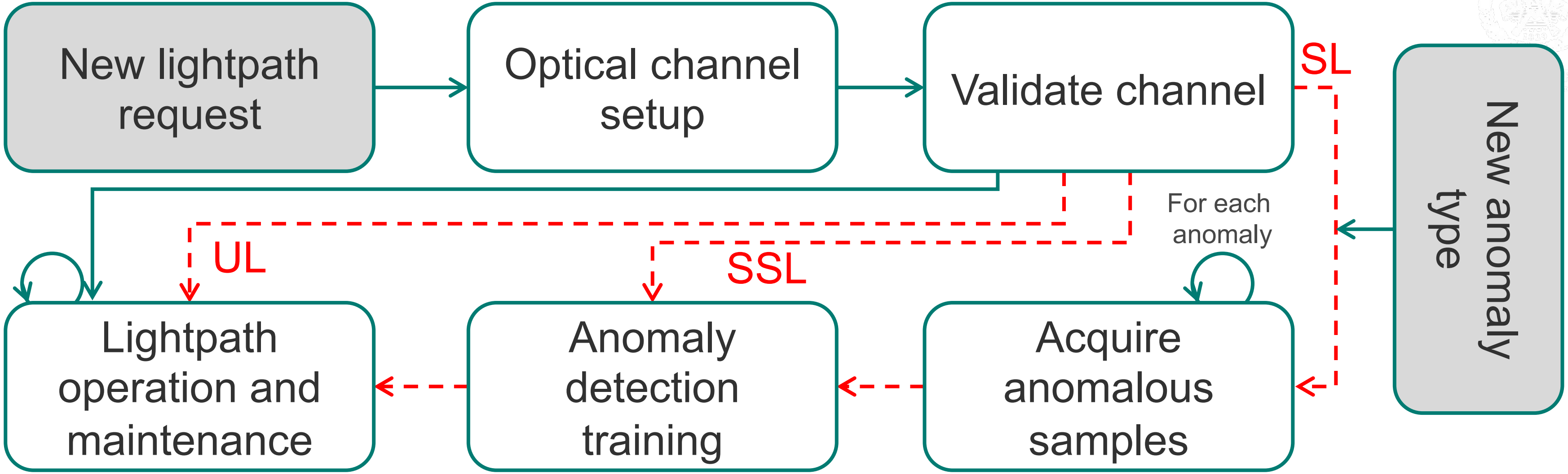
- **A small amount of data is labeled**
  - E.g. the normal operating conditions are known
- The algorithm is trained to detect outliers
- **One-class support vector machine (OCSVM)**
  - Infers the properties of normal cases and distinguishes them from abnormal ones

Unsupervised learning

- **No labeled data**
  - The dataset has no clear input/output nor strictly defined normal/abnormal conditions
- The algorithm learns to identify similarities among different inputs
- **Density-Based Spatial Clustering of Applications with Noise (DBSCAN)**
  - Monitoring samples are separated into clusters and outliers

M. Furdek, et al., “Machine learning for optical network security monitoring: A practical perspective,” IEEE/Optica JLT, April 2020.

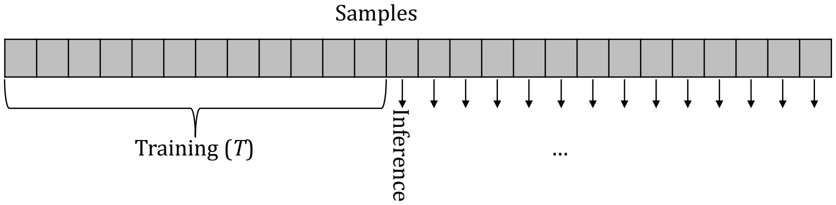
ML workflow



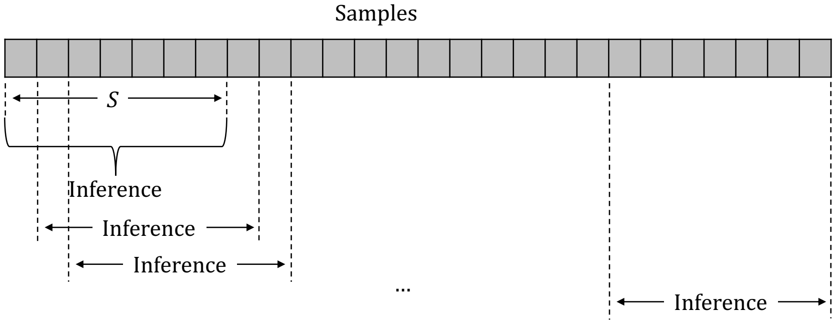
M. Furdek, et al., “Machine learning for optical network security monitoring: A practical perspective,” IEEE/Optica JLT, April 2020.

Timeline comparison

<u>Supervised and semi-supervised learning</u>

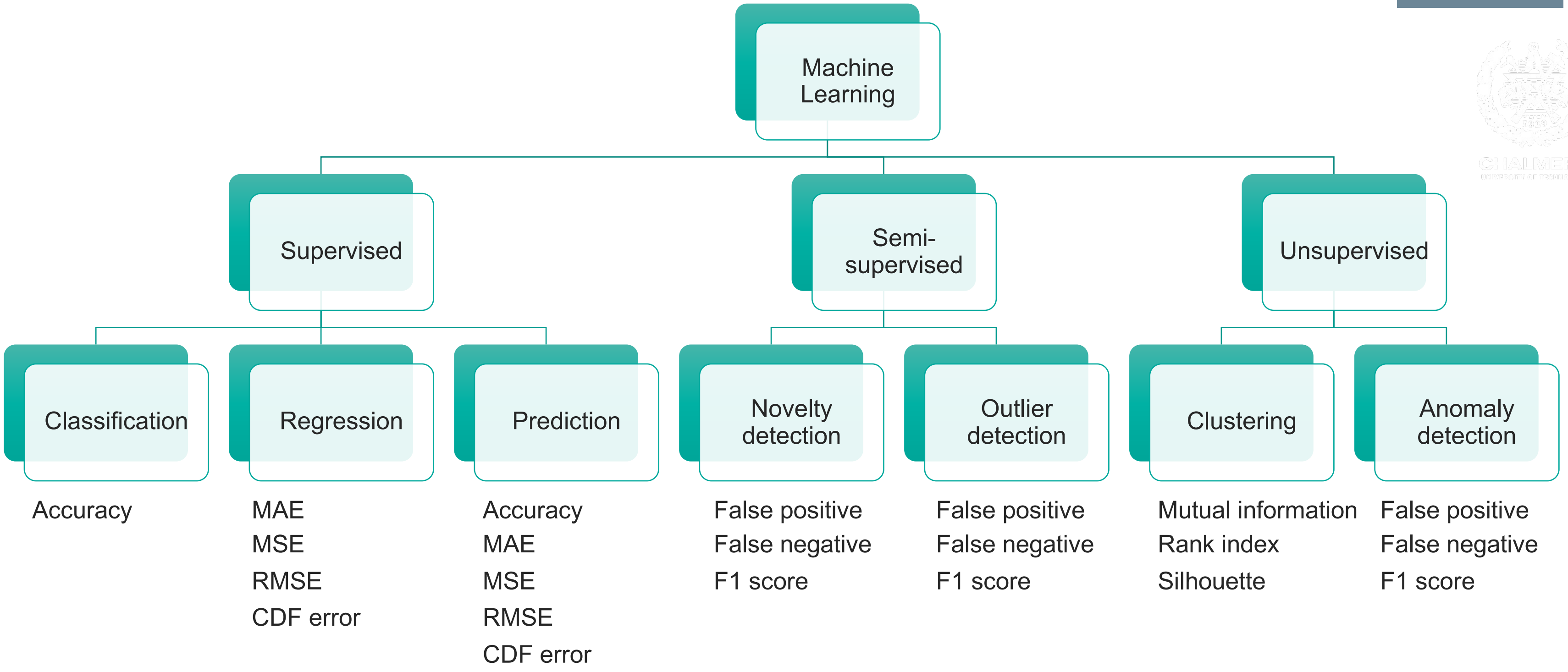


<u>Unsupervised learning</u>

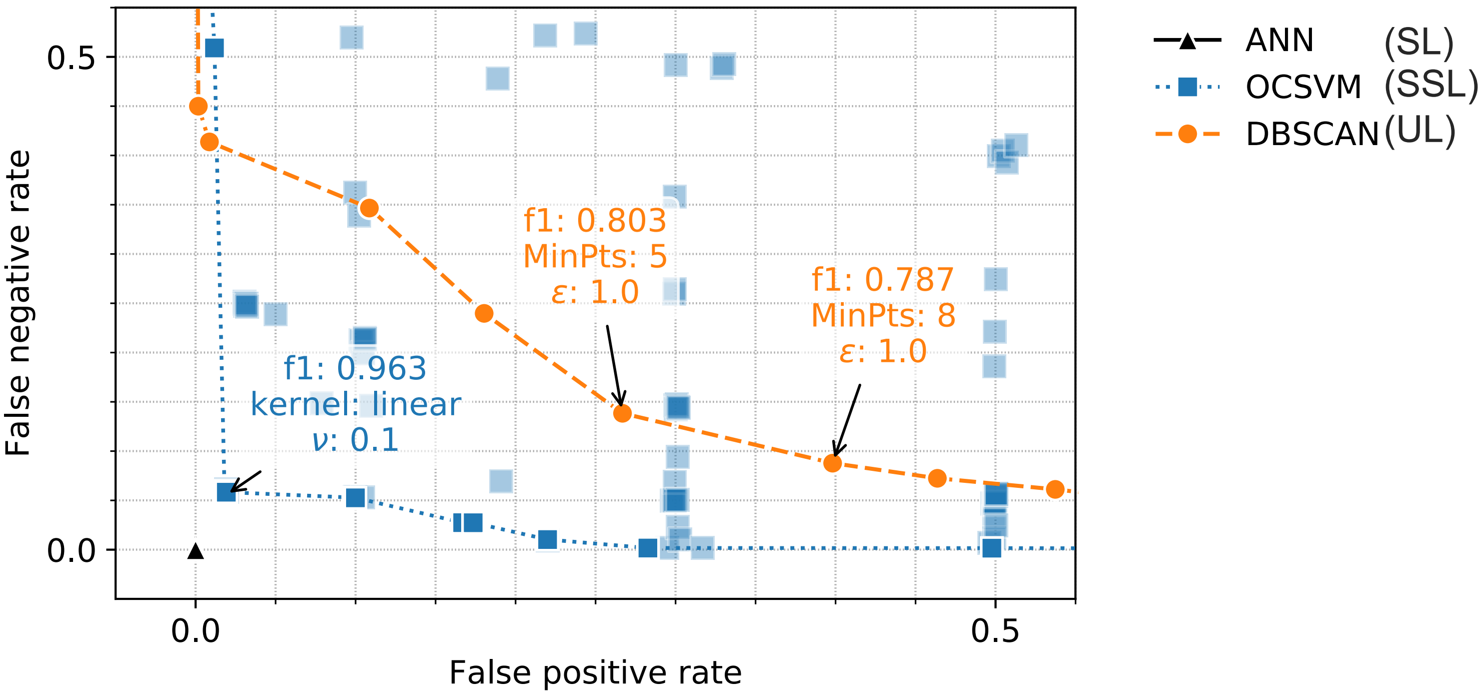


C. Natalino, et al., “Root Cause Analysis for Autonomous Optical Network Security Management,” IEEE TNSM, Sep. 2022.

Evaluation metrics



Accuracy comparison



M. Furdek, et al., “Machine learning for optical network security monitoring: A practical perspective,” IEEE/Optica JLT, April 2020.

Demystifying: Machine Learning

Myth: Machine Learning is suitable for every problem

Demystifying: Machine Learning

Myth: Machine Learning is suitable for every problem

Reality: Properties of the problem need to be carefully analyzed

Not suitable

- Accurate analytical model available
- Fast (enough) analytical model
- Certain and known in parameters
- Controlled behavior and scenario
- Good one-size-fits-all solution

Suitable

- Accurate (enough) models not available
- Relatively slow analytical model
- Uncertain or unknown parameters
- Uncontrolled behavior and scenario
- Need for individualized analysis

Setup Google Drive/Colab

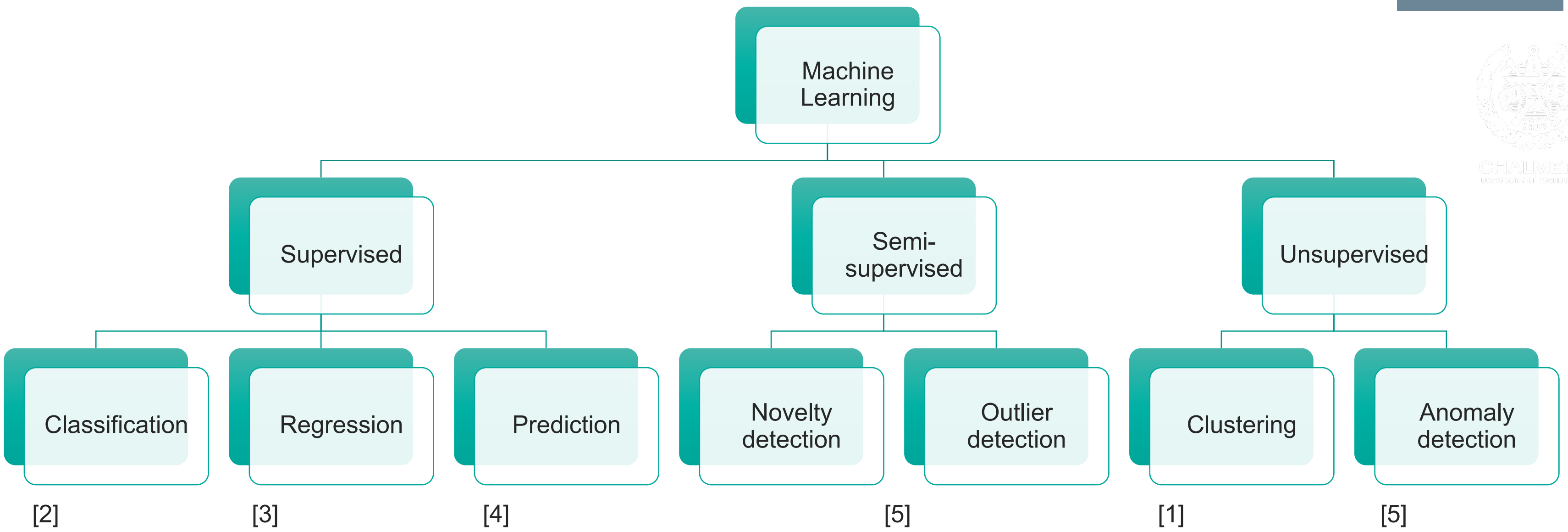
Links at:
https://github.com/carlosnatalino/demystifying-ml

Download file *Demystifying_ML_Part1_01.ipynb* and upload on your own Google Drive

Open the file with Google Colab

Run the code

Use cases



[1] L. Gifre et al., "Slice Grouping for Transport Network Slices Using Hierarchical Multi-domain SDN Controllers," 2023 Optical Fiber Communications Conference and Exhibition (OFC), San Diego, CA, USA, 2023, doi: 10.1364/OFC.2023.M3Z.9.
[2] T. Panayiotou, et al., "Performance analysis of a data-driven quality-of-transmission decision approach on a dynamic multicast- capable metro optical network," in Journal of Optical Communications and Networking, vol. 9, no. 1, pp. 98-108, Jan. 2017, doi: 10.1364/JOCN.9.000098.
[3] M. Ibrahimi et al., "Machine learning regression for QoT estimation of unestablished lightpaths," in Journal of Optical Communications and Networking, vol. 13, no. 4, pp. B92-B101, April 2021, doi: 10.1364/JOCN.410694.
[4] N. Di Cicco, et al., "Uncertainty-Aware QoT Forecasting in Optical Networks with Bayesian Recurrent Neural Networks," ICC 2023 - IEEE International Conference on Communications, Rome, Italy, 2023, pp. 441-446, doi: 10.1109/ICC45041.2023.10278767.
[5] M. Furdek, et al., "Machine learning for optical network security monitoring: A practical perspective," IEEE/OSA JLT, April 2020.

General data exploration and preparation

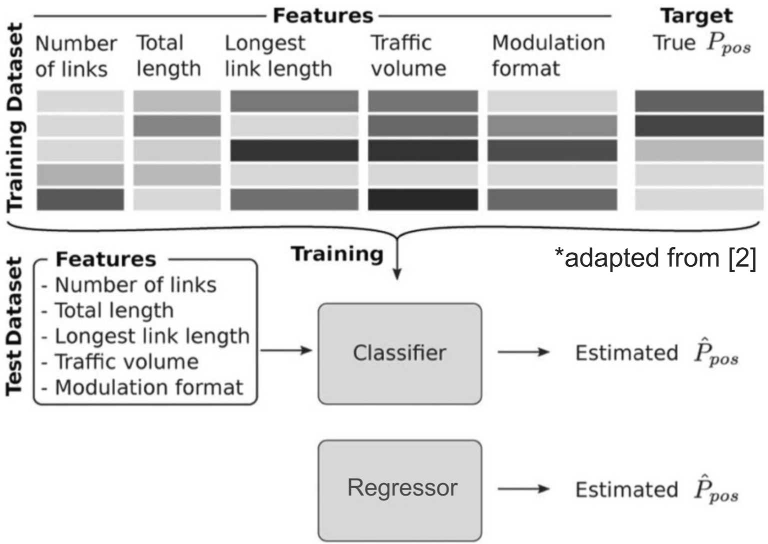
- Let us move back to Google Colab

- Open the file Demystifying_ML_Part1_01.ipynb

Applying supervised learning for performance prediction and estimation

Use case: quality-of-transmission estimation

- Motivation: uncertainty in physical layer parameters [1]
- Task: estimate the end-to-end QoT of an unestablished lightpath
- Dataset generated with the EGN model [3]
- Nobel-EU topology [4]
- Two supervised learning alternatives
  - Classification: does it work or not?
  - **Regression**: what is the expected QoT, e.g., GSNR?
- Download and open the file *Demystifying_ML_Part1_02.ipynb*



*adapted from [2]

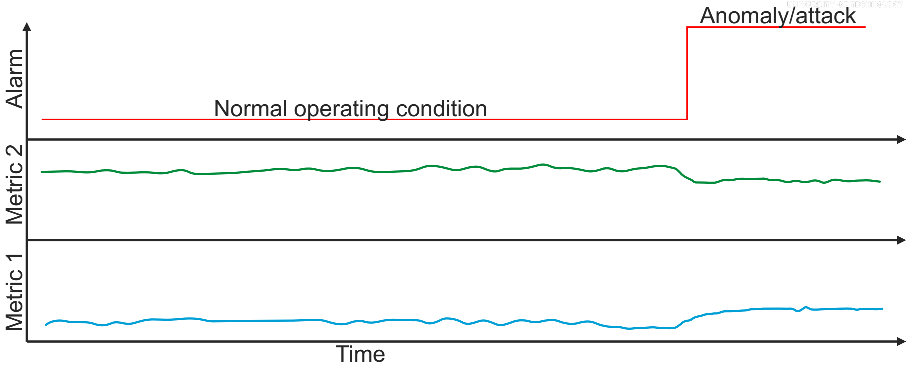
[1] M. Lonardi, et al., "The perks of using machine learning for QoT estimation with uncertain network parameters," Optica APC, paper NeM3B.2, 2020.
[2] C. Rottondi, et al., "Machine-learning method for quality of transmission prediction of unestablished lightpaths," in IEEE/Optica JOCN, vol. 10, no. 2, pp. A286-A297, Feb. 2018, doi: 10.1364/JOCN.10.00A286.
[3] M. Ranjbar Zefreh, et al., "Accurate Closed-Form Real-Time EGN Model Formula Leveraging Machine-Learning Over 8500 Thoroughly Randomized Full C-Band Systems," in Journal of Lightwave Technology, vol. 38, no. 18, pp. 4987-4999, 15 Sept.15, 2020, doi: 10.1109/JLT.2020.2997395.
[4] Orlowski, Sebastian, et al. "SNDlib 1.0—Survivable network design library." Networks: An International Journal 55.3 (2010): 276-286.

Applying semi-supervised and unsupervised learning for anomaly detection

Use case: anomaly detection on lightpaths

- Motivation: each lightpath has different characteristics with no single threshold to be set
- Task: detect autonomously anomalies that affect the lightpath operating conditions
- Two alternatives
  - Semi-supervised learning
  - Unsupervised learning

- Open the file Demystifying_ML_Part1_03.ipynb



Final considerations

References

- M. Furdek, C. Natalino, F. Lipp, D. Hock, A. D. Giglio and M. Schiano, "Machine Learning for Optical Network Security Monitoring: A Practical Perspective," in Journal of Lightwave Technology, vol. 38, no. 11, pp. 2860-2871, 1 June1, 2020, doi: 10.1109/JLT.2020.2987032.
- C. Natalino, M. Schiano, A. D. Giglio and M. Furdek, "Root Cause Analysis for Autonomous Optical Network Security Management," in IEEE Transactions on Network and Service Management, vol. 19, no. 3, pp. 2702-2713, Sept. 2022, doi: 10.1109/TNSM.2022.3198139.
- L. Gifre et al., "Slice Grouping for Transport Network Slices Using Hierarchical Multi-domain SDN Controllers," 2023 Optical Fiber Communications Conference and Exhibition (OFC), San Diego, CA, USA, 2023, doi: 10.1364/OFC.2023.M3Z.9.
- T. Panayiotou, et al., "Performance analysis of a data-driven quality-of-transmission decision approach on a dynamic multicast- capable metro optical network," in Journal of Optical Communications and Networking, vol. 9, no. 1, pp. 98-108, Jan. 2017, doi: 10.1364/JOCN.9.000098.
- M. Ibrahimi et al., "Machine learning regression for QoT estimation of unestablished lightpaths," in Journal of Optical Communications and Networking, vol. 13, no. 4, pp. B92-B101, April 2021, doi: 10.1364/JOCN.410694.
- N. Di Cicco, et al., "Uncertainty-Aware QoT Forecasting in Optical Networks with Bayesian Recurrent Neural Networks," ICC 2023 - IEEE International Conference on Communications, Rome, Italy, 2023, pp. 441-446, doi: 10.1109/ICC45041.2023.10278767.
- M. Lonardi, et al., “The perks of using machine learning for QoT estimation with uncertain network parameters,” Optica APC, paper NeM3B.2, 2020.
- C. Rottondi, et al., "Machine-learning method for quality of transmission prediction of unestablished lightpaths," in IEEE/Optica JOCN, vol. 10, no. 2, pp. A286-A297, Feb. 2018, doi: 10.1364/JOCN.10.00A286.
- M. Ranjbar Zefreh, et al., "Accurate Closed-Form Real-Time EGN Model Formula Leveraging Machine-Learning Over 8500 Thoroughly Randomized Full C-Band Systems," in Journal of Lightwave Technology, vol. 38, no. 18, pp. 4987-4999, 15 Sept.15, 2020, doi: 10.1109/JLT.2020.2997395.
- Orlowski, Sebastian, et al. "SNDlib 1.0—Survivable network design library." Networks: An International Journal 55.3 (2010): 276-286.

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