

## Francesco Musumeci

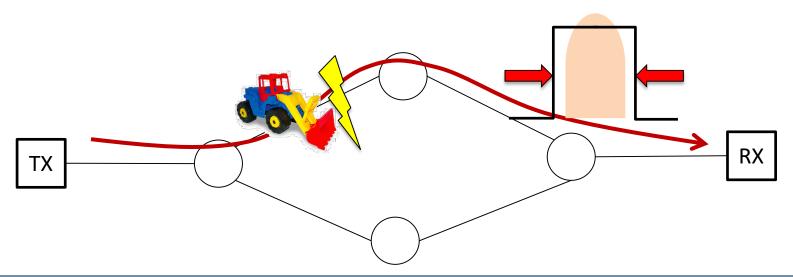
Dipartimento di Elettronica, Informazione e Bioingegneria (DEIB)

Politecnico di Milano, Milano, Italy

### Background

Two main failure types in optical networks

- Hard-failures
  - Sudden events, e.g., fiber cuts, power outages, etc.
  - Unpredictable, require «protection» (reactive procedures)
- "Soft"-failures:
  - Gradual transmission degradation due to equipment malfunctioning, filter shrinking/misalignment...
  - Trigger early network reconfiguration (proactive procedures)



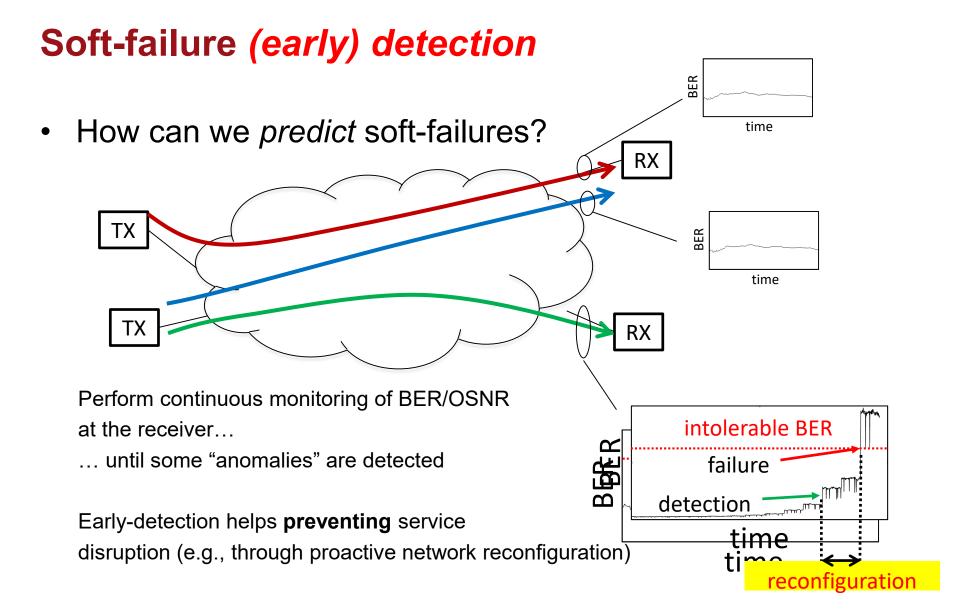
## Failure management in optical networks Background

- Monitoring signal quality in several network locations is expensive
- OSNR (Optical Signal to Noise Ratio) and/or BER (Bit Error Rate) at the receiver are relatively "cheap" to measure, and are directly impacted in case of failures

In this lab, two types of soft-failures:

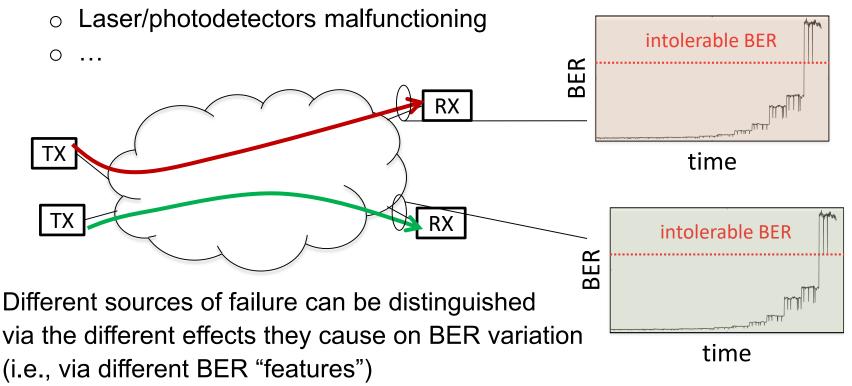
- Excessive attenuation, due to fiber ageing, optical amplifiers malfunctioning, etc.
- Extra filtering, due to filters misalignment, laser drift (carrier wavelength used by transmitting devices is not perfectly aligned with the DWDM grid), optical switches malfunctioning, etc.

•	Different	flavours	of failure	management	in o	ptical	networks	3



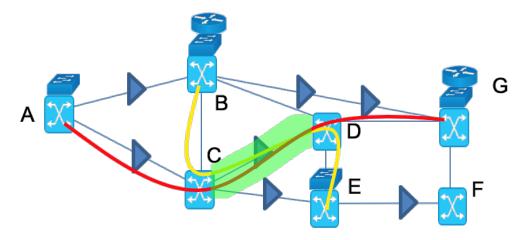
### Soft-failure cause identification

- How can we identify the cause of the failure?
  - Failures can be caused by different sources
    - Filters shrinking/misalignment
    - Excessive attenuation (e.g., due to amplifier malfunctioning)



### Soft-failure localization

- How can we identify the location of the failure?
  - A single failure may affect multiple lightpaths
    - Leverage information on failure-cause on each lightpath in combination with routing information
    - No need for monitoring in the entire network (monitors can be deployed only at the receivers)
  - Even with information on a single lightpath (e.g., at the receiver), does the impact change with distance between failure and receiver?



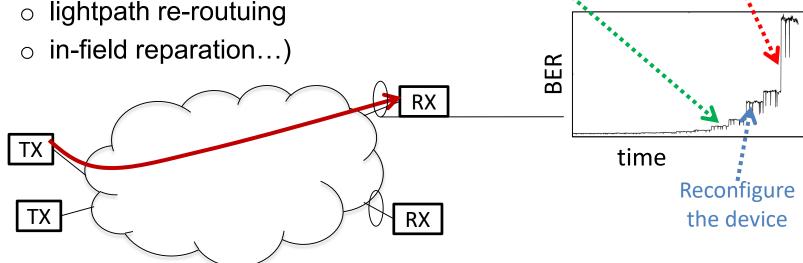
## Soft-failure magnitude estimation

- What is the failure magnitude (i.e., severity)?
  - Different failures magnitude can affect the network differently

 According to the severity, different actions can be triggered to solve the failure Replace

device restart/reconfiguration

lightpath re-routuing



Reset the

device

the device

## **Handling soft-failures**

Summary Lab's focus

- **1. (Early) Detection** (Whether or not?)
  - Predict/assess if OSNR/BER is/will be intolerable
  - Allows early/quick activation of proactive procedures
- 2. Identification (Which cause?)
  - e.g., filter misalignment, laser drift, fiber bending, amplifier malfunctioning ..
  - Reduced Mean Time To Repair (MTTR)
- 3. Localization of soft-failures (Where?)
  - e.g., which node/link along the path?
- 4. Magnitude estimation (How much?)
  - Triggers the proper reaction (e.g., device restart/reconfiguration, lightpath re-routuing, in-field reparation...)

## Failure management in optical networks Source paper

JOURNAL OF LIGHTWAVE TECHNOLOGY, VOL. 37, NO. 16, AUGUST 15, 2019

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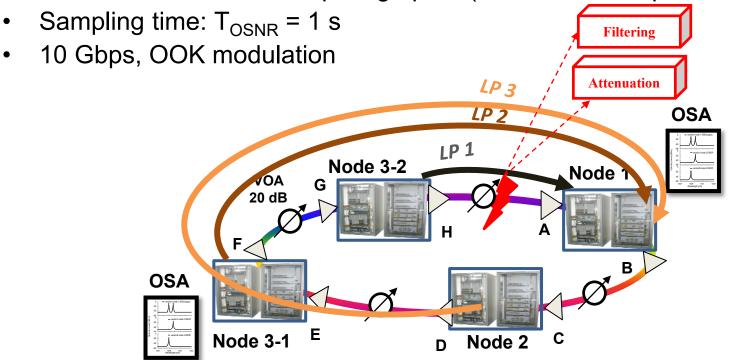
## A Tutorial on Machine Learning for Failure Management in Optical Networks

Francesco Musumeci , Cristina Rottondi , Giorgio Corani, Shahin Shahkarami, Filippo Cugini , and Massimo Tornatore

(Invited Tutorial)

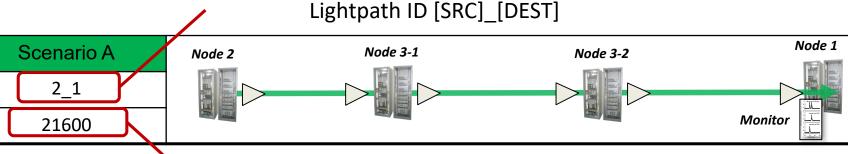
## **Testbed Setup**

- Opt. Net. testbed with 4 Reconfigurable Optical Add/Drop Multiplexers (ROADMs)
  - OSNR collected for different lightpaths at different monitoring locations
  - Center-wavelength @194.8 THz, BW=100 GHz
  - 6 hours of measurement per lightpath (with some exceptions...)



Dataset (1)

	Description	Magnitude	Location (link)
Scenario A	No failures	-	-
Scenario B	Excessive attenuation	11 dB	3-2 – 1
Scenario C	Extra filtering	12.5 GHz	3-2 – 1



Number of OSNR samples (6hours)

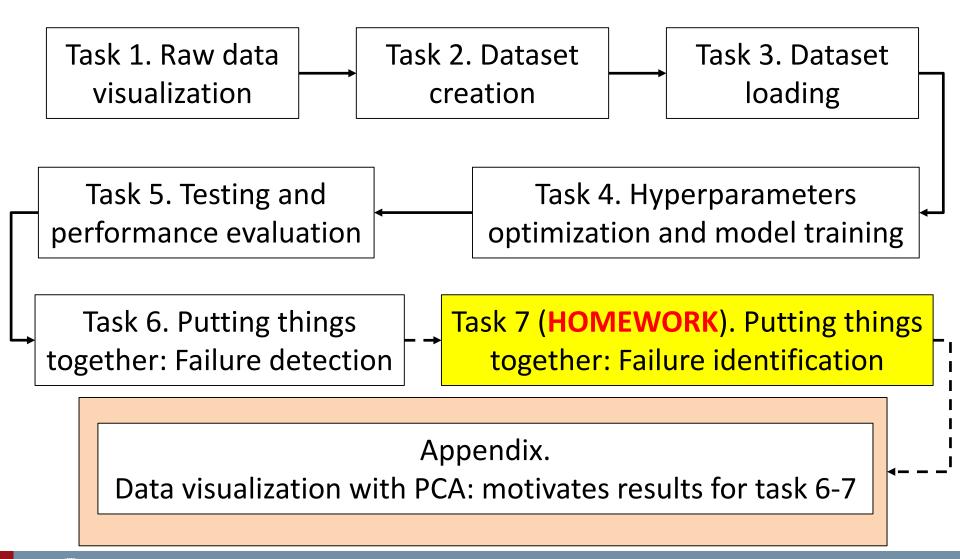
Scenario B	Node 2	Node 3-1	Node 3-2	Node 1
2_1			11 d	В
21600				Monitor
Scenario C	Node 2	Node 3-1	Node 3-2	Node 1
Scenario C 2_1	Node 2	Node 3-1	Node 3-2	

Dataset (2)

Raw dataset: how it looks like

```
AUTHENTICATE CRAM-MD5.
readv
             Tag for memo use.
 'eady
 OPC is OK (1).
                                                                                                 Collected data from OSA
       ,PK_WL[THZ],LEVEL[dBm],3.0dB WD[nm],CRT WL WL[NM],3.0dB PB[nm],RIPPLE[dB],CROSS TK[L][dB],CROSS TK[R][dB],OFFSET WL[n
   OFFSET LEVEL [dBm].NOISE [dBm] [NBW].OSNR [dB]
2019/07/26 18:47:19 553/194.800/-20.897,236702579,194800939,374929661,25.210, 8.649, 8.636, 0.000, 0.000,-46.876/25.978
2019/07/26 18:47:19 558 194.800,-20.906,241765735,194800940,373790320,25.125, 8.710, 8.682, 0.000, 0.000,-46.864,25.955
2019/07/26 18:47:19 558 194.800,-20.812,234171031,194800950,373663765,25.175, 8.756, 8.744, 0.000, 0.000,-46.864,25.997
2019/07/26 18:47:19 558 194.800,-20.862,<mark>2</mark>35436805,194800948,374676501,25.234, 8.639, 8.592, 0.000, 0.000,-46.861<mark>,</mark>25.996
                                Peak PWR
    Timestamp
                                                                                                      Noise [dBm]
                                   [dBm]
                  Freq [THz]
```

Lab overview

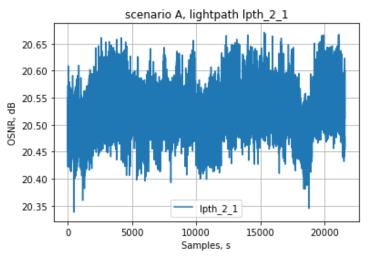


#### Task 1

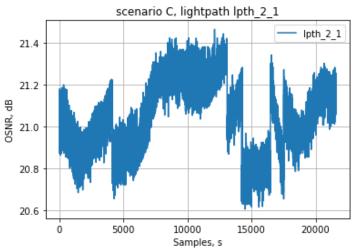
- Visualize OSNR data
  - a) Define a function plot\_scenario() that plots OSNR traces given a file name in input
    - See skeleton code for the details
  - b) Use function plot\_scenario() to plot OSNR figures for scenarios A-B-C
    - Already given in skeleton code

Task 1: expected outputs

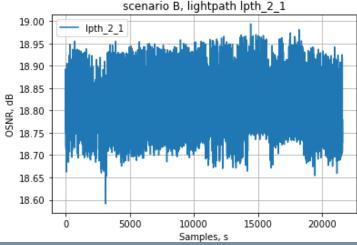
Scenario A No failure



## Scenario C Extra filtering (12.5 GHz)



Scenario B Excessive attenuation (11 dB)



#### Task 2

#### **Dataset creation**

- Each data point will consist of a "window" of duration W, including a sequence of consecutive OSNR samples
- From each window, we compute the following features:
  - 1. mean:  $\mu = \frac{1}{W} \sum_{i=1}^{W} OSNR_i$
  - 2. Root mean square:

$$RMS = \sqrt{\frac{1}{W} \sum_{i=1}^{W} (OSNR_i)^2}$$

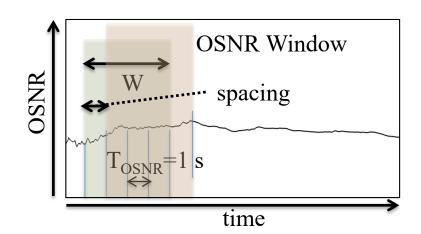
3. peak-to-peak:

$$Ptp = Max - min$$

4. Standard dev:

$$STD = \sqrt{\frac{1}{W} \sum_{i=1}^{W} |OSNR_i - \mu|^2}$$

- 5. Max:  $M = \max_{i \in [1,W]} (OSNR_i)$
- 6. min:  $m = \min_{i \in [1,W]} (OSNR_i)$



#### Task 2

- 2. Create the window dataset
  - a) Define a function create\_window\_dataset() that takes in input raw data file, window length and spacing and creates a features .dat file in a subfolder called 'Datasets'
    - See skeleton code for the details
    - Task 2a') is given in the skeleton to test function create\_window\_dataset()
  - b) Use function *create\_window\_dataset()* to generate features files for scenarios A-B-C using window duration =10,20,...,100 seconds and window spacing = 1 second

### Task 2: expected outputs

```
Scenario A - No failure – W=10
  mean,RMS,ptp,std,max,min
  20.509,20.509,0.123,0.032,20.549,20.426
  20.512,20.512,0.124,0.034,20.55,20.426
  20.513,20.513,0.124,0.036,20.55,20.426
Scenario B Excessive attenuation (11 dB) – W=10
  mean,RMS,ptp,std,max,min
  18.815,18.815,0.141,0.052,18.893,18.752
  18.816,18.816,0.141,0.052,18.893,18.752
  18.824,18.824,0.141,0.048,18.893,18.752
Scenario C Extra filtering (12.5 GHz) – W=10
  mean,RMS,ptp,std,max,min
  21.058,21.058,0.254,0.08,21.151,20.897
  21.062,21.062,0.254,0.08,21.151,20.897
  21.054,21.054,0.248,0.074,21.145,20.897
```



#### Task 3

- 3. Load dataset
  - a) Define a function load\_window\_dataset() that takes in input window data file, and label to be assigned and returns numpy arrays with features and labels
    - See skeleton code for the details
  - b) Use function *load\_window\_dataset()* with datasets of scenarios A-B-C using **window length = 10 and spacing = 1**. Assign labels so as to generate a **binary dataset** useful for **failure detection problem** (0=normal, 1=failure)
    - Already given in skeleton code
  - c) Do a 80/20 split of the dataset into train/test with balanced classes and check consistency between no of positives (i.e., datapoints with y=1) across train/test/full sets

Task 3b)-c): expected outputs

While appending data from the 3 scenarios

#### Final dataset (X,y)

```
print(X)
print(y)
print(X.shape)
print(y.shape)
```

#### Train/test datasets

```
5 print(X.shape)
6 print(y.shape)
7 print(Xtrain.shape)
8 print(ytrain.shape)
9 print(Xtest.shape)
10 print(ytest.shape)
```

```
current shape of X: (21591, 6)
current shape of y: (21591,)
current shape of X: (43182, 6)
current shape of y: (43182,)
current shape of X: (64773, 6)
current shape of y: (64773,)
[[20.509 20.509 0.123 0.032 20.549 20.426]
[20.512 20.512 0.124 0.034 20.55 20.426]
[20.513 20.513 0.124 0.036 20.55 20.426]
...
[21.143 21.143 0.157 0.043 21.233 21.076]
[21.142 21.142 0.157 0.043 21.233 21.076]
[21.144 21.144 0.157 0.042 21.233 21.076]]
[0 0 0 ... 1 1 1]
(64773, 6)
(64773,)
```

```
(64773, 6)
(64773,)
(51818, 6)
(51818,)
(12955, 6)
(12955,)
# positives in y = 43182
# positives in ytrain = 34545
# positives in ytest = 8637
```

- 4. Algorithms hyperparameters optimization and training
  - a) Define function train\_classifier\_logistic() that performs hyperparameter optimization with 5-fold crossvalidation and training and returns the trained model
    - See skeleton code for the details
    - Part of the function is given in the skeleton
    - Task 4a') is given in the skeleton to test function train\_classifier\_logistic()

Task 4a): expected output

Crossval time [s]: 35.141

Best hyperparams during crossval: {'regularization': 1000, 'max iter': 100,

'score': 0.7942222357373689}

[[0.78013447 0.76573791 0.76573791]

[0.78372395 0.78671519 0.78671519]

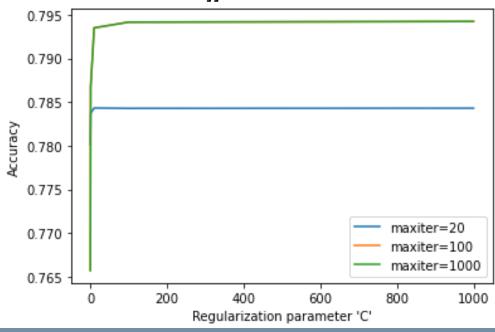
[0.7843222 0.79348889 0.79348889]

[0.7842836 0.79414504 0.79414504]

[0.7843029 0.79422224 0.79422224]]

Score of the final model: 0.7945115596896831

Training time [s]: 0.608



#### Task 4

- 4. Algorithms hyperparameters optimization and training
  - b) Consider a new dataset (X\_norm, y) instead of (X,y) with normalized features and repeat train/test split and hyperparameters selection with crossvalidation with the normalized dataset

**Expected output:** 

What are the main changes you observe before and after normalization?

#### Crossval time [s]: 16.492

Best hyperparams during crossval: {'regularization':

1000, 'max iter': 100, 'score': 0.7944345034044575}

[[0.78445725 0.78414848 0.78414848]

[0.78619413 0.7888573 0.7888573 ]

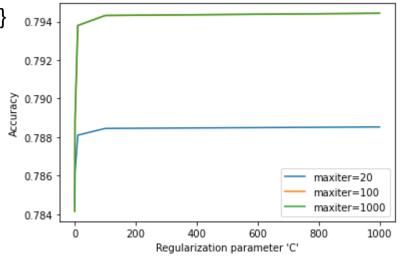
[0.78810466 0.79379768 0.79379768]

[0.78845202 0.79431872 0.79431872]

[0.78852921 0.7944345 0.7944345 ]]

Score of the final model: 0.7946852445096299

Training time [s]: 0.273



 From now on, we will always use the normalized dataset (X\_norm,y)

- 4. Algorithms hyperparameters optimization and training
  - Define function train\_classifier\_DNN() that performs hyperparameter optimization and training for DNN with given hyperparameters space
    - See skeleton code for the details
  - d) Use function train\_classifier\_DNN() to perform hyperparameters selection with crossvalidation for DNN and considering the normalized dataset retrieved in task 4b)
    - Already given in skeleton code

## Task 4c)-d): expected output

Crossval time [s]: 730.453

Best hyperparams: {'activation': 'logistic', 'layers': 1, 'neurons': 2, 'score': 1.0}

- [[[1. 1. 1.]
  - [1. 1. 1. ] [1. 1. 1. ]
- [[0.91296387 1. 1.
- [0.84625627 1. 1.
- [0.85051708 1. 1. ]]

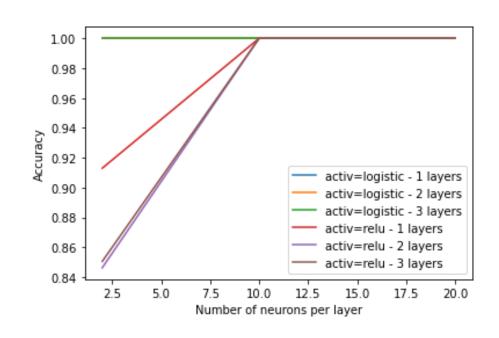
Score of the final model: 1.0

Best activation: logistic.

Best no of layers: 1.

Best no of neurons: 2

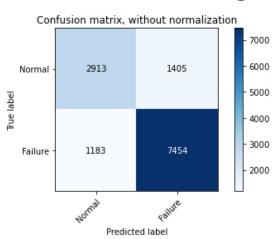
Training time [s]: 18.067

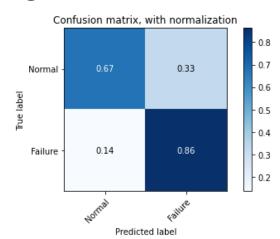


- 5. Test and performance evaluation
  - a) Define function performance\_eval() that takes in input ground truth and predicted labels, prints results in a result file passed in input, and returns global metrics
    - See skeleton code for the details
  - b) Perform prediction using the optimized logistic regression and DNN models and **considering the normalized dataset retrieved in task 4b**). Then, evaluate performance of the two models using function *performance eval()*

### Task 5: expected outputs

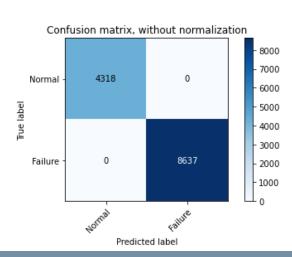
### Logistic regression

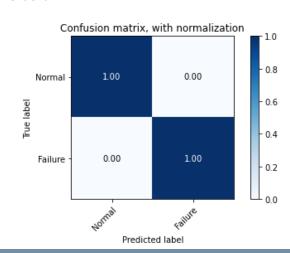




Logistic regression metrics (accuracy, global precision, global recall, global f1score): (0.8002315708220764, 0.798000045310873, 0.8002315708220764, 0.7988635583610862)

#### DNN



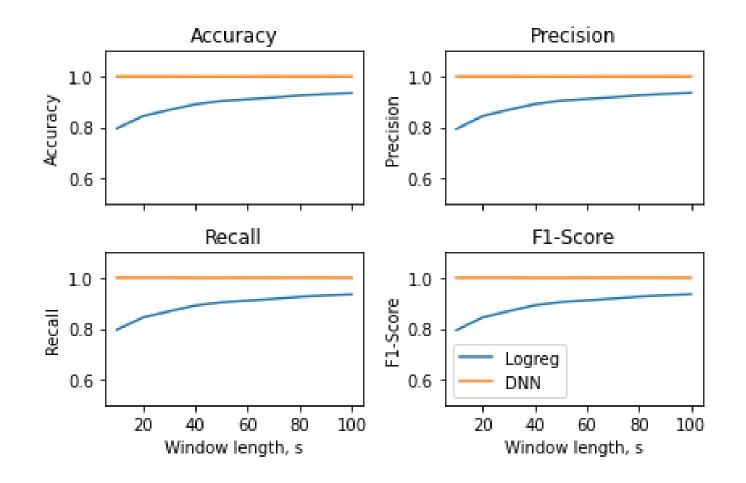


DNN metrics (accuracy, global precision, global recall, global f1score): (1.0, 1.0, 1.0, 1.0)

#### Task 6

- 6. Putting things together: failure detection
  - a) For window length in range(10,101,10) and window spacing = 1, repeat dataset load (task 3b), data normalization and dataset split (task 4b), training of logistic regression and DNN with best hyperparameters (as those obtained in tasks 4b) and 4d), i.e., no need to re-do hyperparameter optimization), test and performance evaluation (task 5b), store global results (accuracy, precision, recall and F1-score) in proper lists for each ML algorithm
  - b) Plot the 4 metrics vs window length in 4 separate graphs, where each graph includes one curve for each ML algorithm
    - Already given in skeleton code

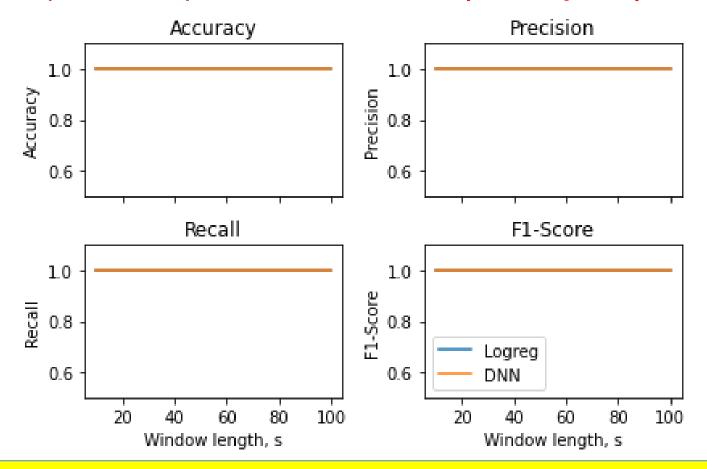
Task 6b): expected outputs



## Failure management in optical networks Task 7 – HOMEWORK (max 1 point)

7. Putting things together: **failure identification**a)-b) Repeat tasks 6a)-6b) but considering only failure classes (scenario B: Attenuation, scenario C: Filtering)

Task 7: expected outputs – **HOMEWORK (max 1 point)** 



We found that logistic regression for failure detection fails (has lower accuracy) for some window sizes (e.g. length = 10 s) compared to failure identification.

Why?

## **Appendix**

Doing a transformation with PCA and 2 components, we are able to visualize data on a 2D graph

Already given in skeleton code

What can we observe and conclude regarding the previous question?

We found that logistic regression for failure detection fails (has lower accuracy) for some window sizes compared to failure identification.

Why?

ANSWER

