



**POLITECNICO**  
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# **Machine Learning Methods for Communication Networks and Systems**

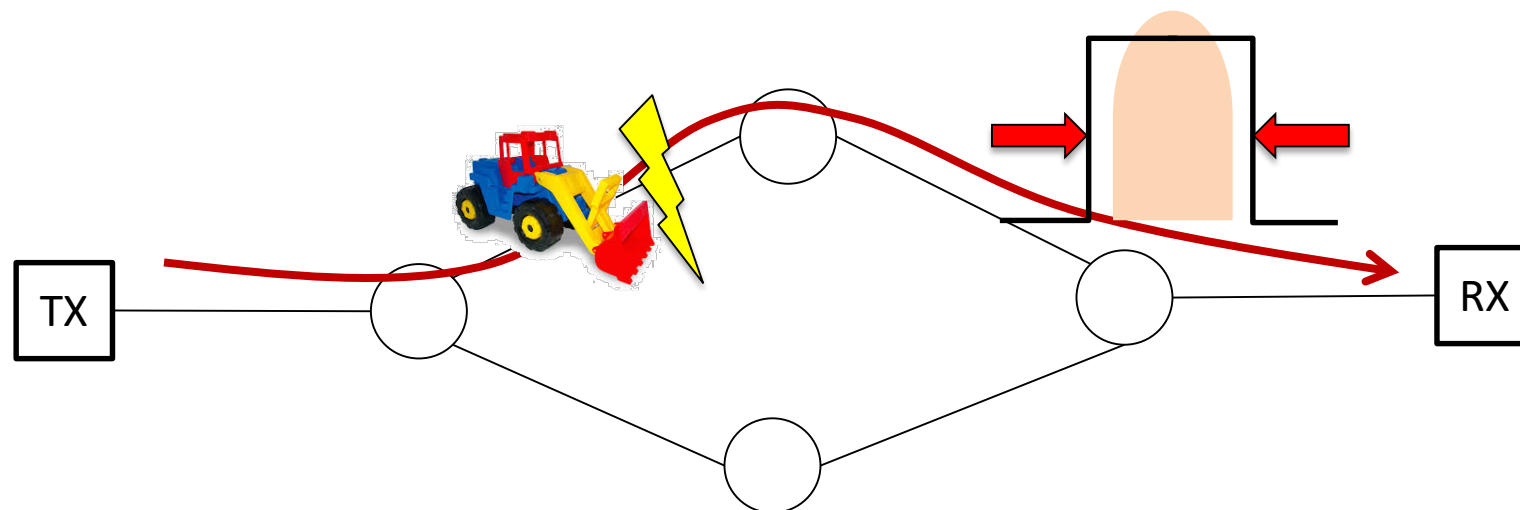
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# Two main failure types in optical networks

- 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*)



# Handling soft-failures

## 1. Early detection (When?)

- «Predict» that BER will go above a threshold
- Allows early/quick activation of proactive procedures

## 2. Identification (Which element?)

- 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?

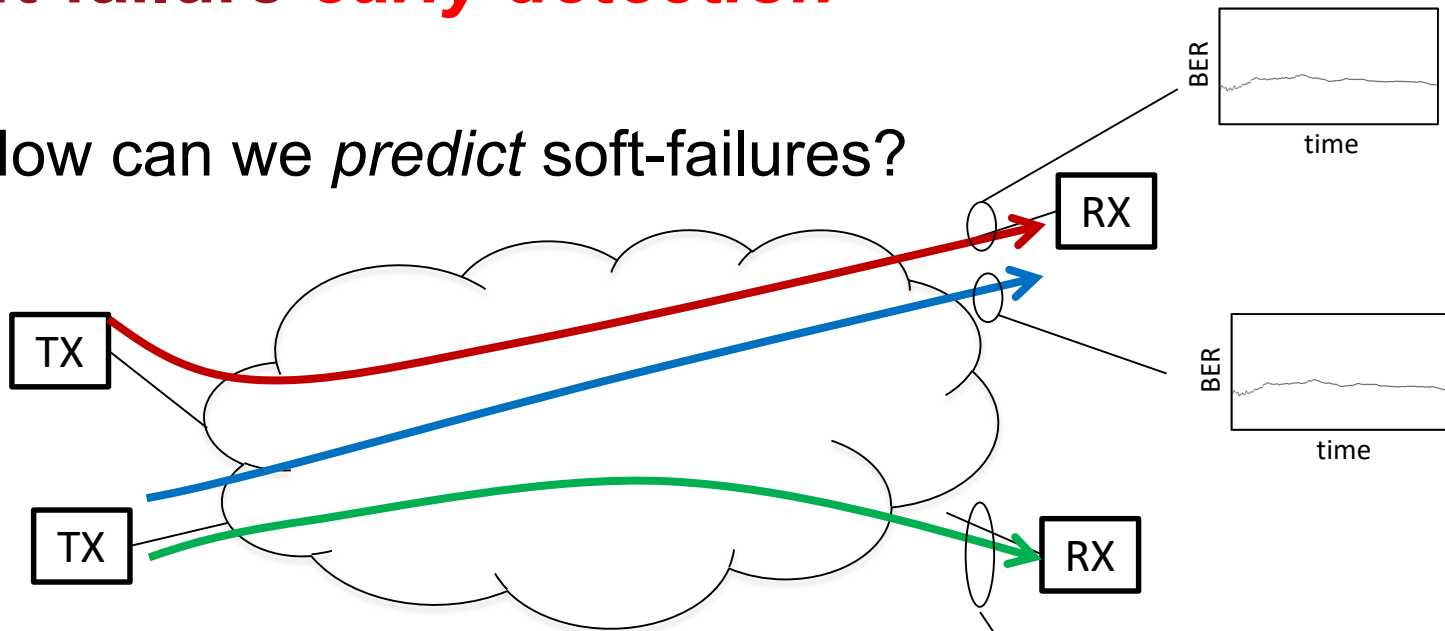
## 4. Magnitude estimation (How much?)

- Triggers the proper reaction (e.g., device restart/reconfiguration, lightpath re-routung, in-field reparation...)



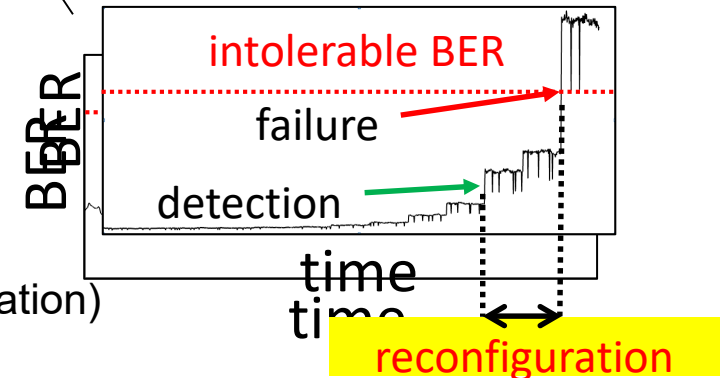
# Soft-failure *early detection*

- How can we *predict* soft-failures?



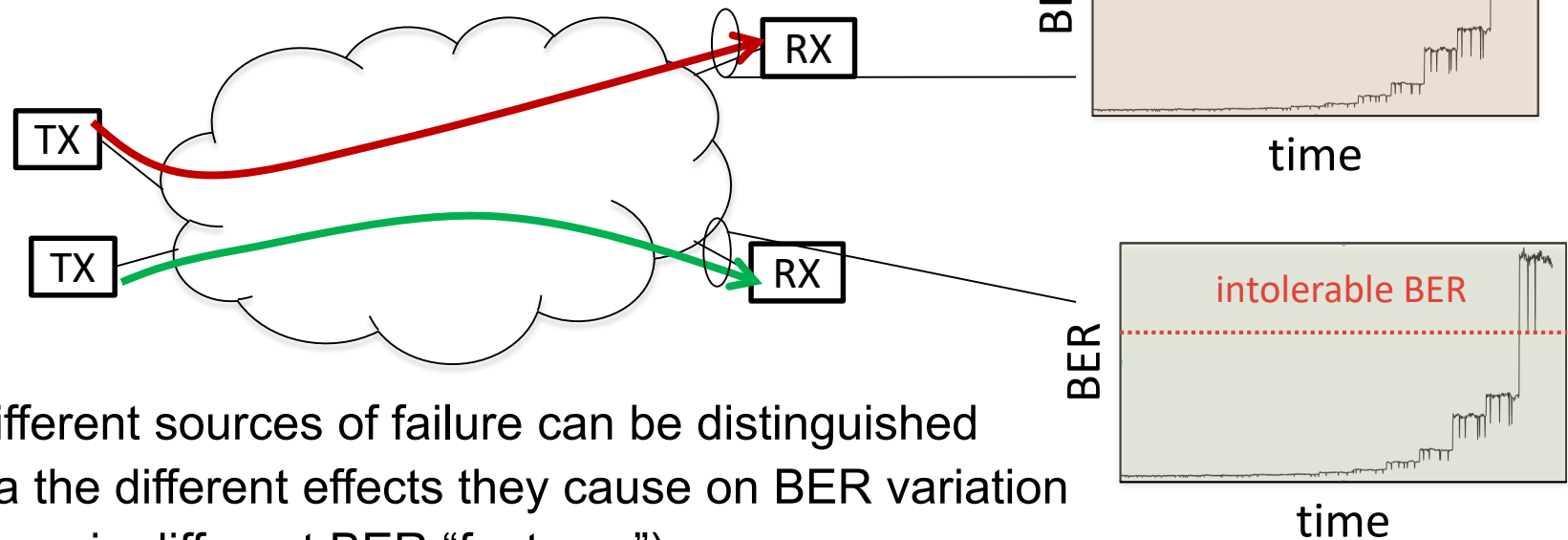
Perform continuous monitoring of Bit Error Rate (BER) at the receiver...  
... until some “anomalies” are detected

Early-detection helps **preventing** service disruption (e.g., through proactive network reconfiguration)



# Soft-failure *cause identification*

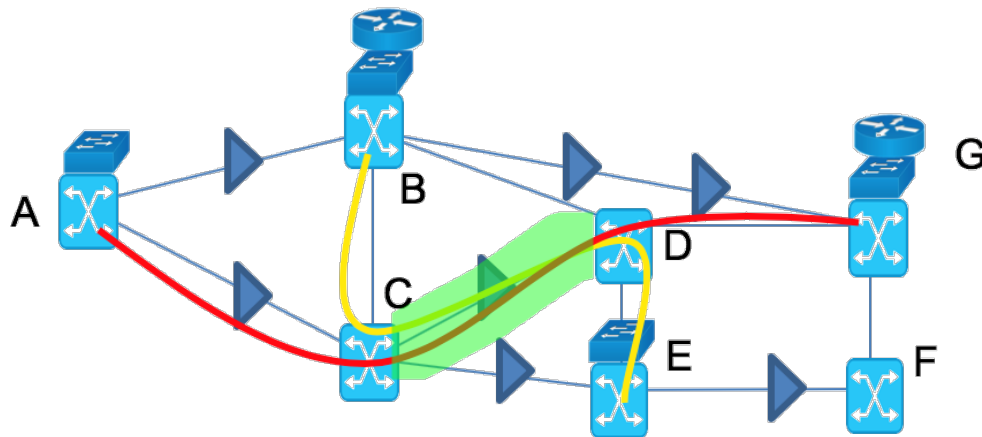
- How can we identify the *cause* of the failure?
  - Failures can be caused by different sources
    - Filters shrinking/misalignment
    - Excessive attenuation (e.g., due to amplifier malfunctioning)
    - Laser/photodetectors malfunctioning
    - ...



Different sources of failure can be distinguished via the different effects they cause on BER variation (i.e., via different BER “features”)

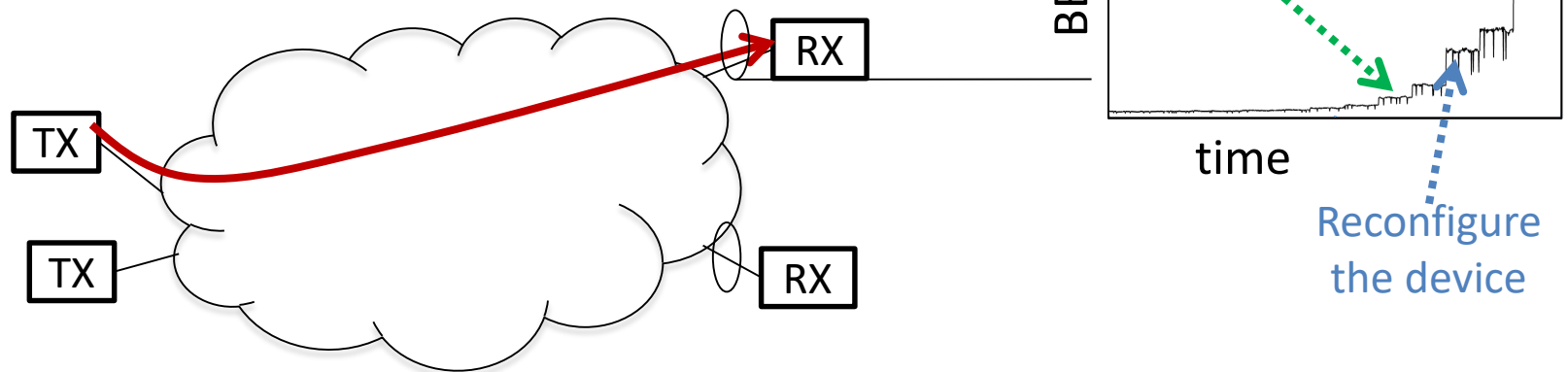
# Soft-failure *localization*

- 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)



# 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
    - device restart/reconfiguration
    - lightpath re-routuing
    - in-field reparation...



# Failure management

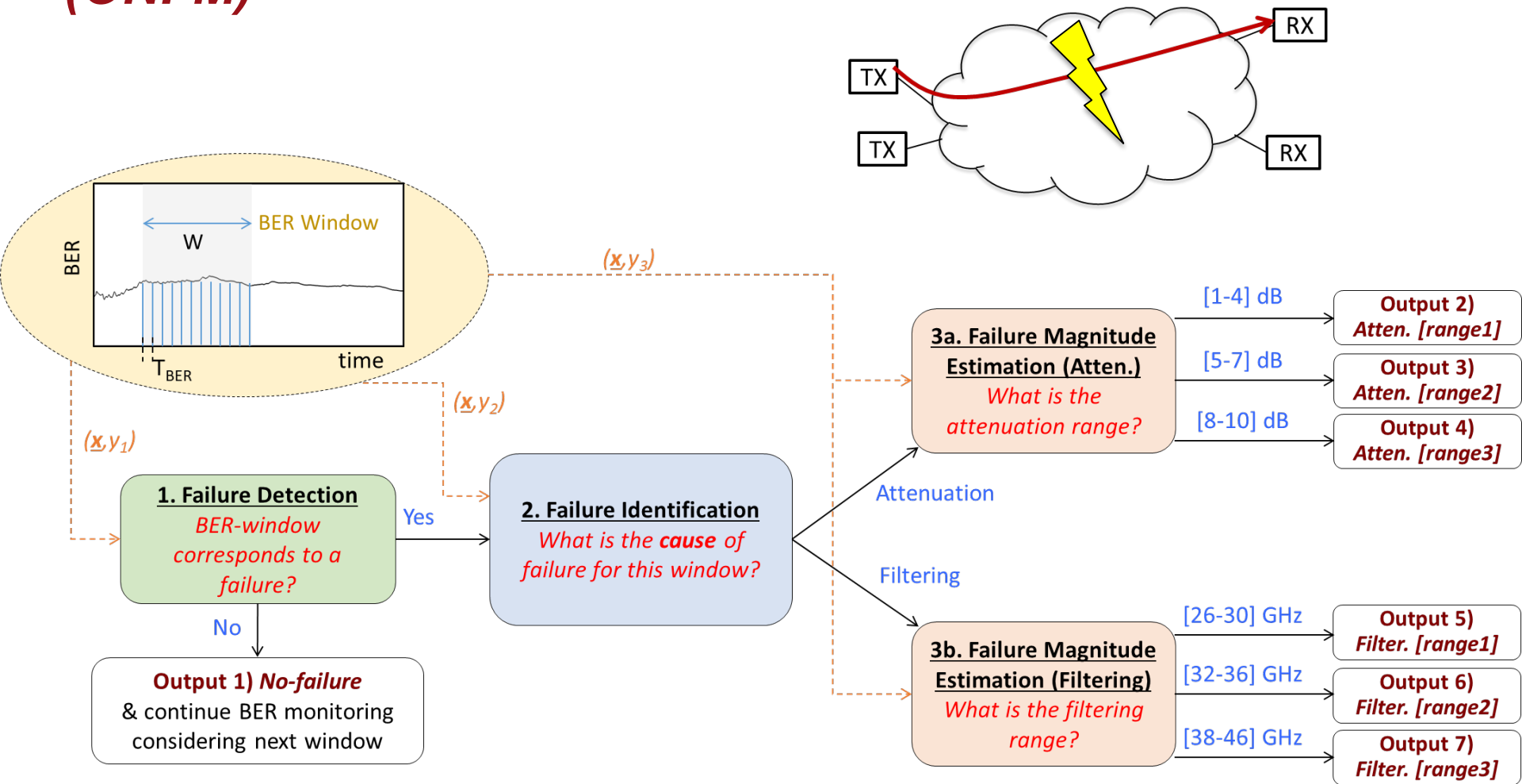
## Sources 1-2

1. F. Musumeci *et al.*, “A Tutorial on Machine Learning for Failure Management in Optical Networks”, *Journal of Lightwave Technology*, vol. 37, n. 16, Aug. 2019
  2. S. Shahkarami *et al.*, “Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks,” in *OFC Conference 2018*, pp. M3A–5
- Paper(s) objective: failure detection, cause identification and magnitude estimation in optical transmission system
    - input
      - monitored BER
    - output
      - failure detection, cause identification and magnitude estimation
    - ML algorithms:
      - ANN
      - SVM
      - RF





# Our study: *Optical Network Failure Management (ONFM)*

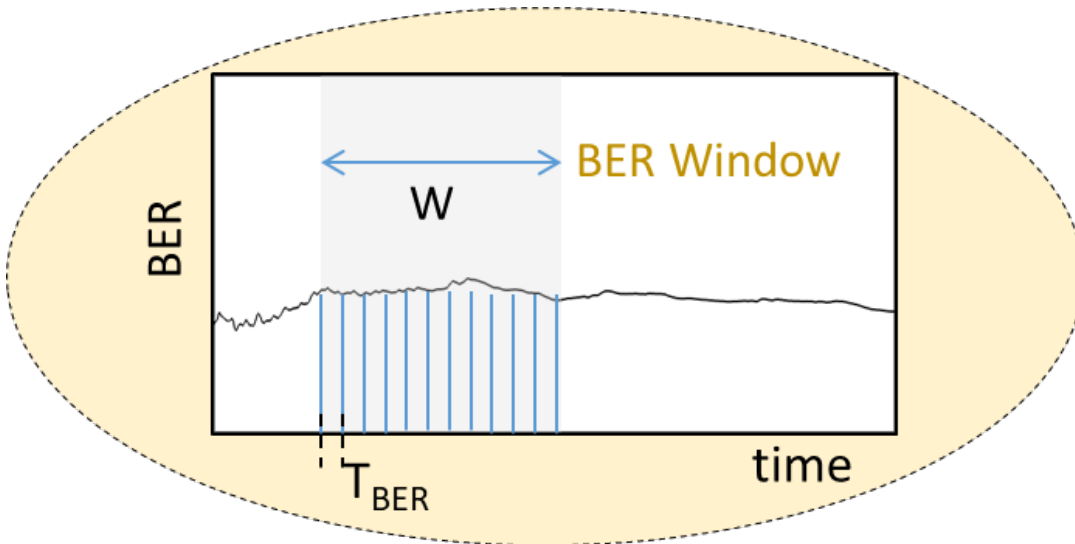


F. Musumeci *et al.*, "A Tutorial on Machine Learning for Failure Management in Optical Networks", *Journal of Lightwave Technology*, vol. 37, n. 16, Aug. 2019



# Window analysis

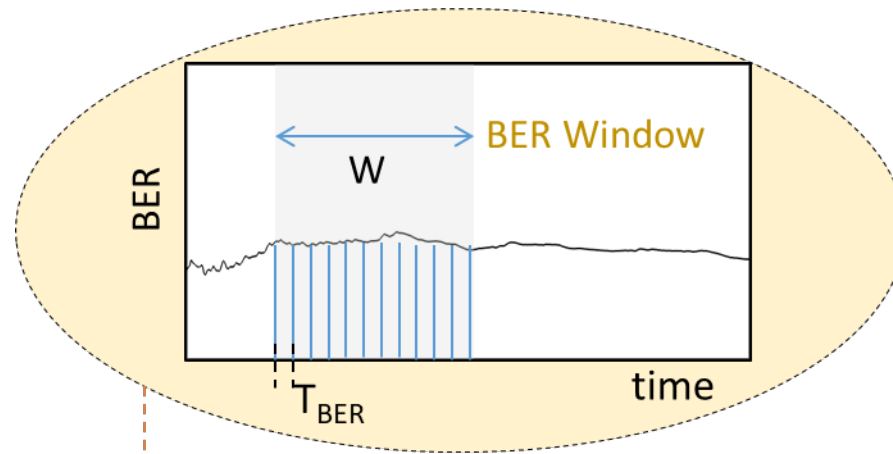
- BER window: two main optimization parameters
  - Window duration,  $W$  (variable)
  - BER sampling period,  $T_{\text{BER}}$  (=2 seconds in our study)
  - Training of the ML algorithms is done for different combinations of these two params



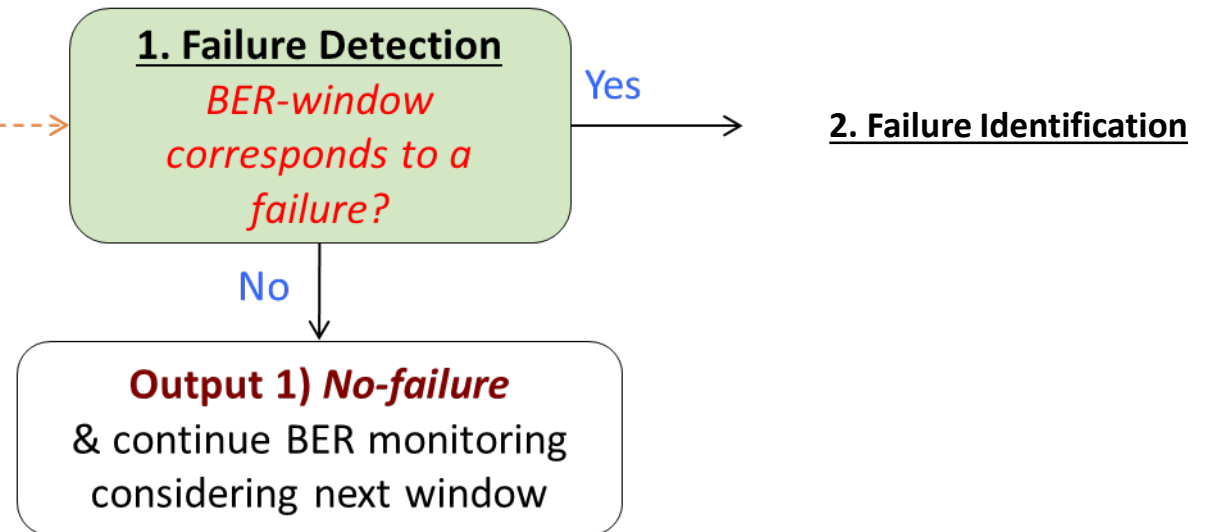
## Features extracted:

- BER statistics:
  - mean
  - min/max
  - standard dev.
  - Peak-to-peak
- Window spectral components after FFT

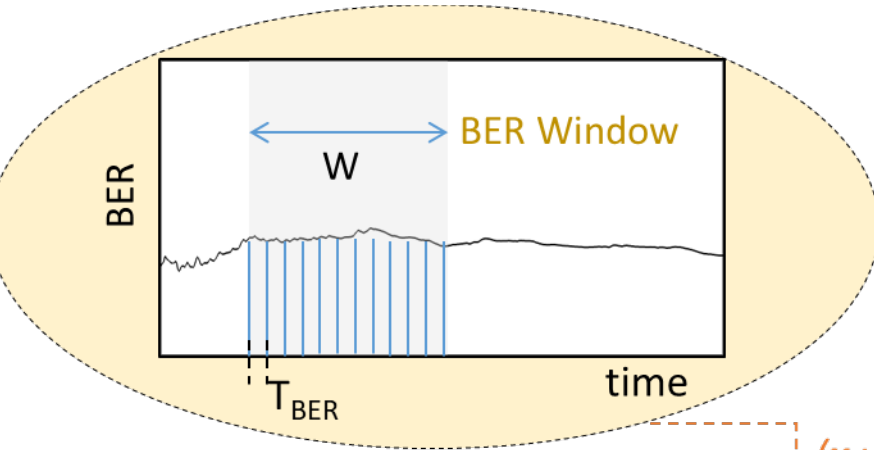
# Failure detection



$(x, y_1)$



# Failure identification



**1. Failure Detection**

Yes

$(x, y_2)$

**2. Failure Identification**

*What is the **cause** of failure for this window?*

**3a. Failure Magnitude Estimation (Attenu.)**

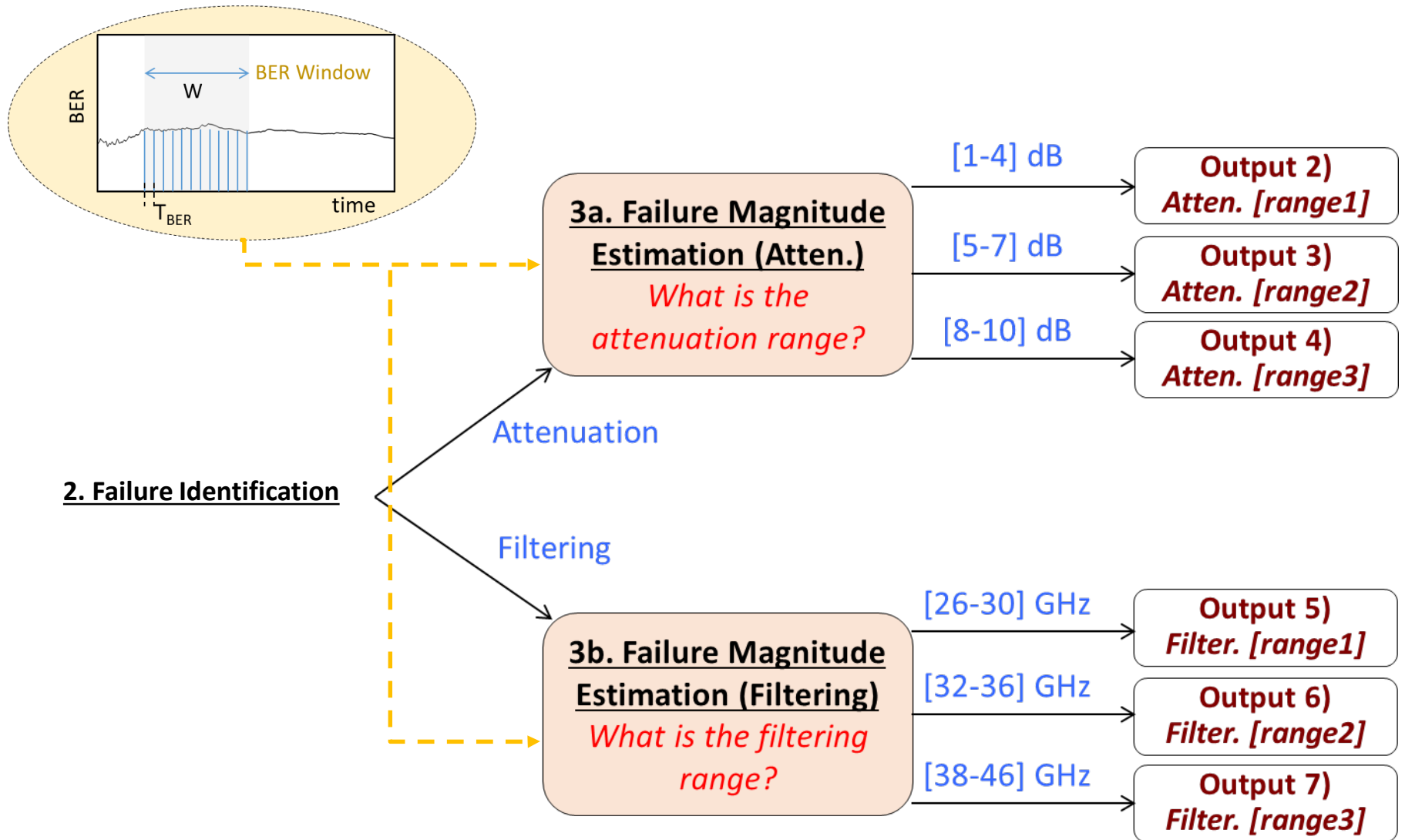
Attenuation

Filtering

**3b. Failure Magnitude Estimation (Filtering)**

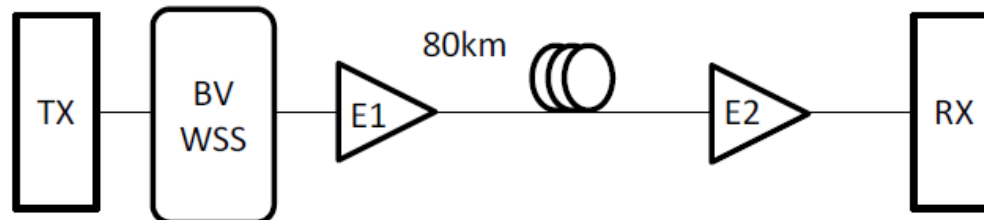


# Failure magnitude estimation



# Testbed setup (1)

- Testbed for real BER traces
  - Ericsson 80 km transmission system
    - 24 hours BER monitoring
    - 2 seconds sampling interval
  - PM-QPSK modulation @ 100Gb/s
  - 2 Erbium Doped Fiber Amplifiers (EDFA) followed by Variable Optical Attenuators (VOAs, not shown)
  - Bandwidth-Variable Wavelength Selective Switch (BV-WSS) is used to emulate **2 types of BER degradation**:
    - **Filter misalignment (*Filtering*)**
    - Additional attenuation in intermediate span, due to EDFA gain-reduction (***Attenuation***)
  - Different failure magnitudes:
    - *Filtering*: 50-to-26 GHz at steps of 2 GHz
    - *Attenuation*: 0-to-10 dB additional attenuation at steps of 1 dB

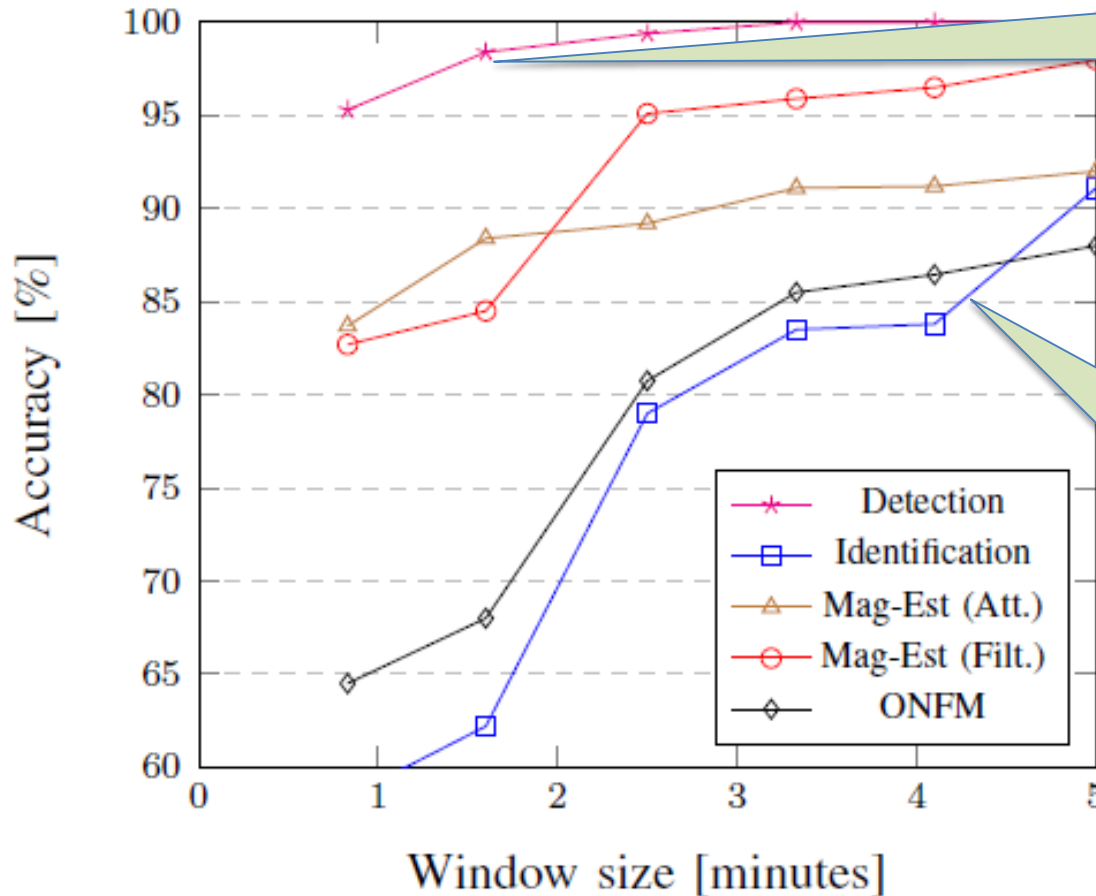


F. Musumeci *et al.*, "A Tutorial on Machine Learning for Failure Management in Optical Networks", *Journal of Lightwave Technology*, vol. 37, n. 16, Aug. 2019



# Results

**Takeway1:** Accuracy always increases with window duration



**Takeway2:** Detection (finding anomalies) is accurate also for in short-time windows

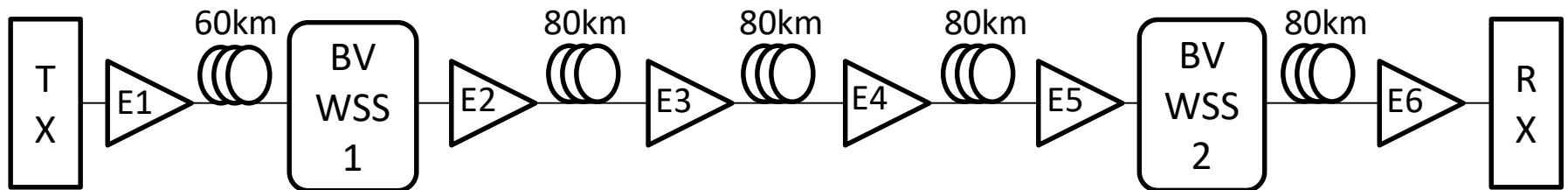
**Takeway3:** Complex tasks (e.g., failure-cause identification) requires more BER info (longer windows) to have sufficient accuracy

F. Musumeci *et al.*, "A Tutorial on Machine Learning for Failure Management in Optical Networks", *Journal of Lightwave Technology*, vol. 37, n. 16, Aug. 2019



# Testbed setup (2)

- Testbed for real BER traces
  - Ericsson 380 km transmission system
    - 24 hours BER monitoring
    - 3 seconds sampling interval
  - PM-QPSK modulation @ 100Gb/s
  - 6 Erbium Doped Fiber Amplifiers (EDFA) followed by Variable Optical Attenuators (VOAs)
  - Bandwidth-Variable Wavelength Selective Switch (BV-WSS) is used to emulate **2 types of BER degradation**:
    - **Filter misalignment**
    - Additional attenuation in intermediate span (e.g., due to **EDFA gain-reduction**)



S. Shahkarami et al, "Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks," in OFC Conference 2018, pp. M3A–5

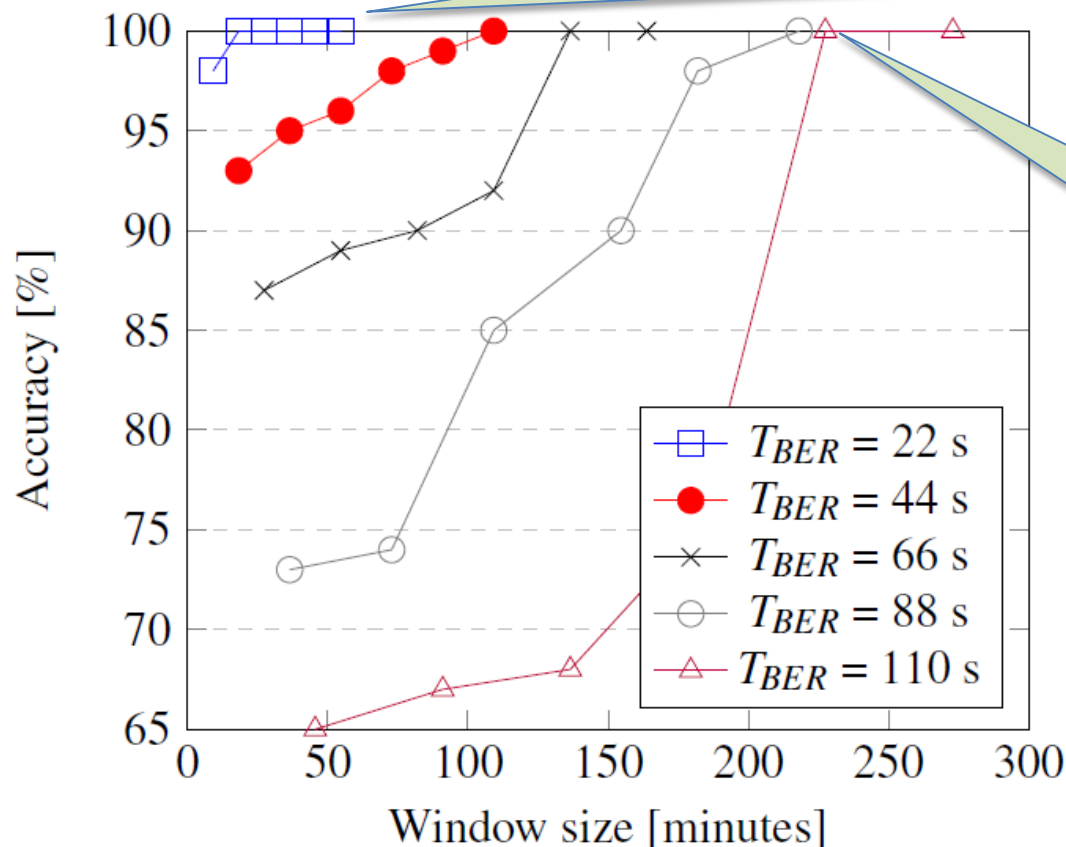




# Numerical results: *Detection*

## Accuracy vs window features

- Binary SVM



**Take-away 1:** Higher performance with low sampling time  
→ Fast monitoring equipment is required

**Take-away 2:** For increasing sampling time, longer “Windows” are needed for high accuracy

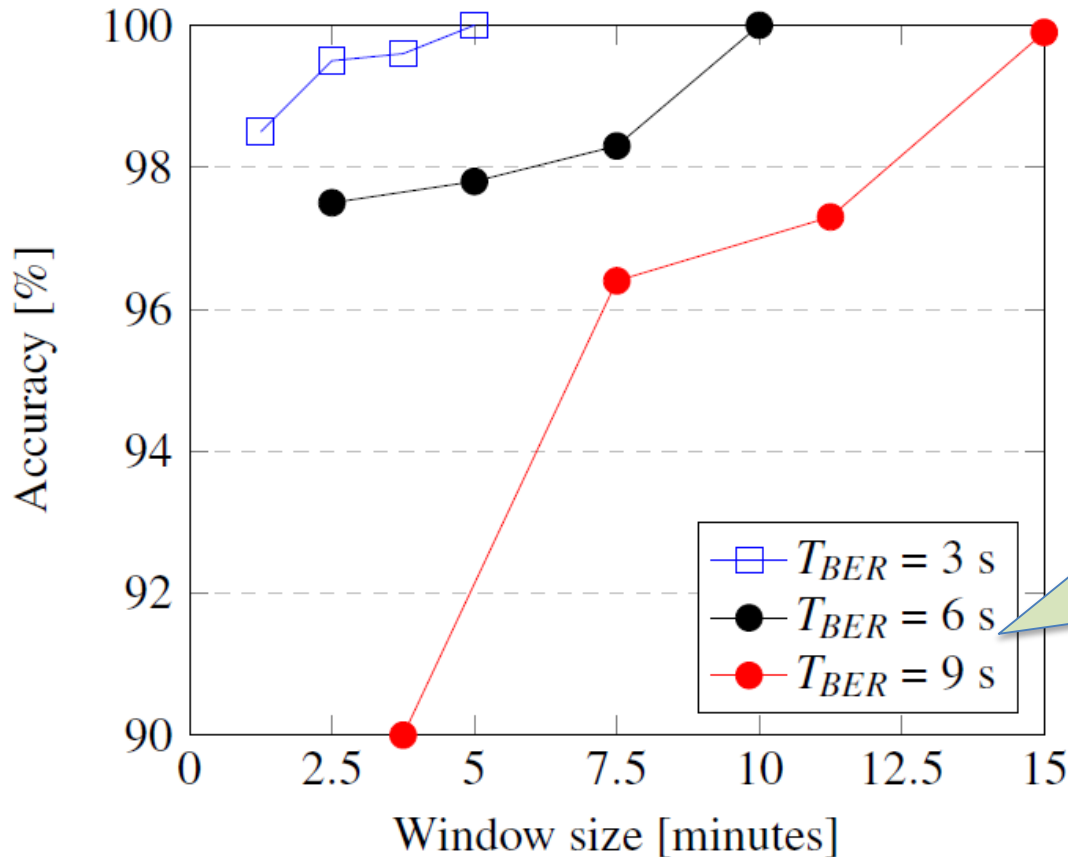
S. Shahkarami et al, “Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks,” in OFC Conference 2018, pp. M3A–5



# Numerical results: *Identification*

## Accuracy vs window features

- Neural Network



**Take-away 3:** To perform failure-cause identification, much smaller sampling period is needed wrt failure detection

S. Shahkarami et al, "Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks," in OFC Conference 2018, pp. M3A-5



# Transfer Learning: Motivation



ML requires training phase and its knowledge does not generalize to *any* condition

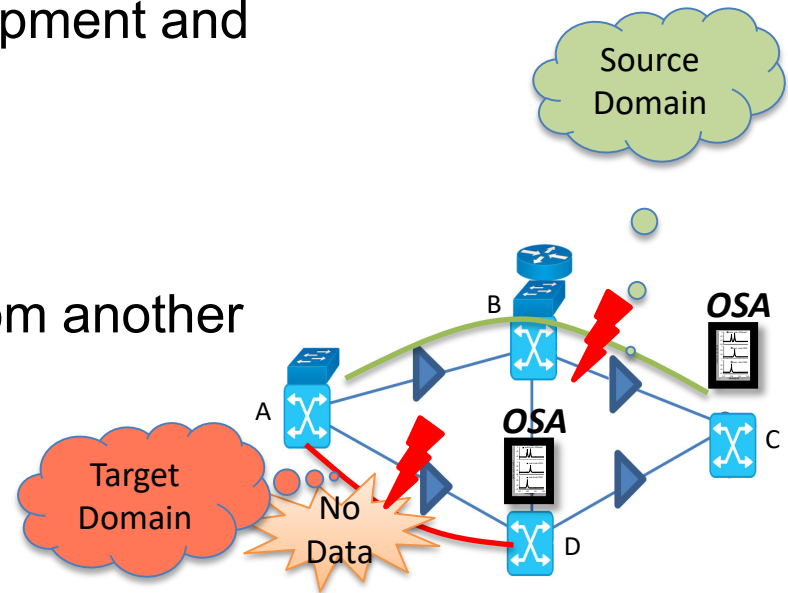
- Data collection issues
  - lack of monitoring equipment (OSA, etc...) at every network node
  - costly acquisition of large datasets
  - **training should be re-done on every link**
- Strategy 1: install new monitoring equipment and generate failures

**COSTLY!** Generating soft-failures requires lot of effort!!!

- Strategy 2: acquire OSNR samples from another lightpath. However...
  - ...different data distributions

TRANSFER LEARNING

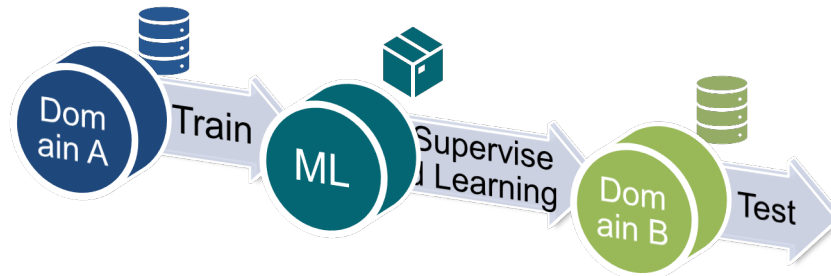
Re-use data from a source domain in a target domain



# Transfer Learning (TL): Principles

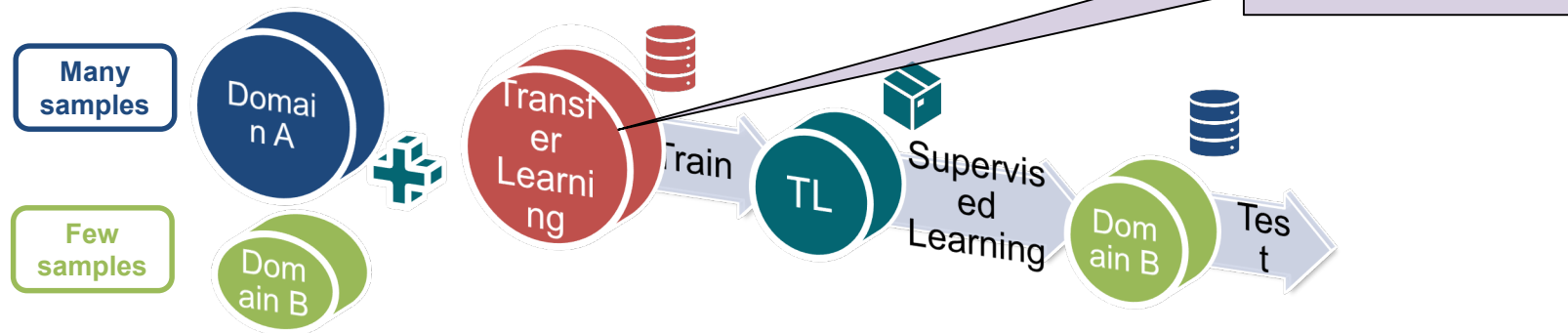
Option 1: **[Pure TL]** no samples from B (target domain) available

→ TRAIN with samples of A (source domain) and TEST with samples of B (target domain)



Option 2: **[Domain Adaptation (DA)]** a few samples from B are available

→ TRAIN with (many) samples of A and (few) of B, and TEST with samples of B

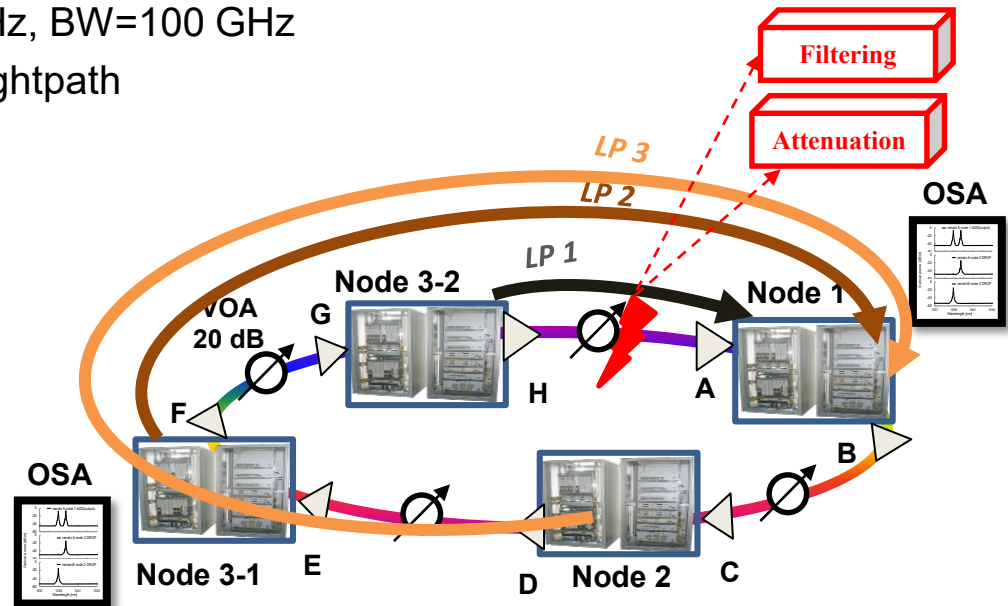


\*Baochen Sun, Jiashi Feng, and Kate Saenko. "Return of Frustratingly Easy Domain Adaptation". In Prof. Of AAAI'16.: (Nov. 2015).



# Testbed Setup

- Opt. Net. testbed @NICT Sendai w/ 4 ROADMs
  - Data collected for 3 lightpaths at the receiver sites (pre-amp)
  - Center-wavelength @194.8 THz, BW=100 GHz
  - 6 hours of measurement per lightpath
  - Sampling time:  $T_{OSNR} = 1$  s
  - 10 Gbps, OOK modulation



# Baseline scenarios

## 1. Target Domain Only (TD Only)

- trains the classifier using all labeled data points in the target domain ( $|TD|=5000$  windows)
- represents an “upper bound” on identification accuracy

## 2. Source Domain (SD Only)

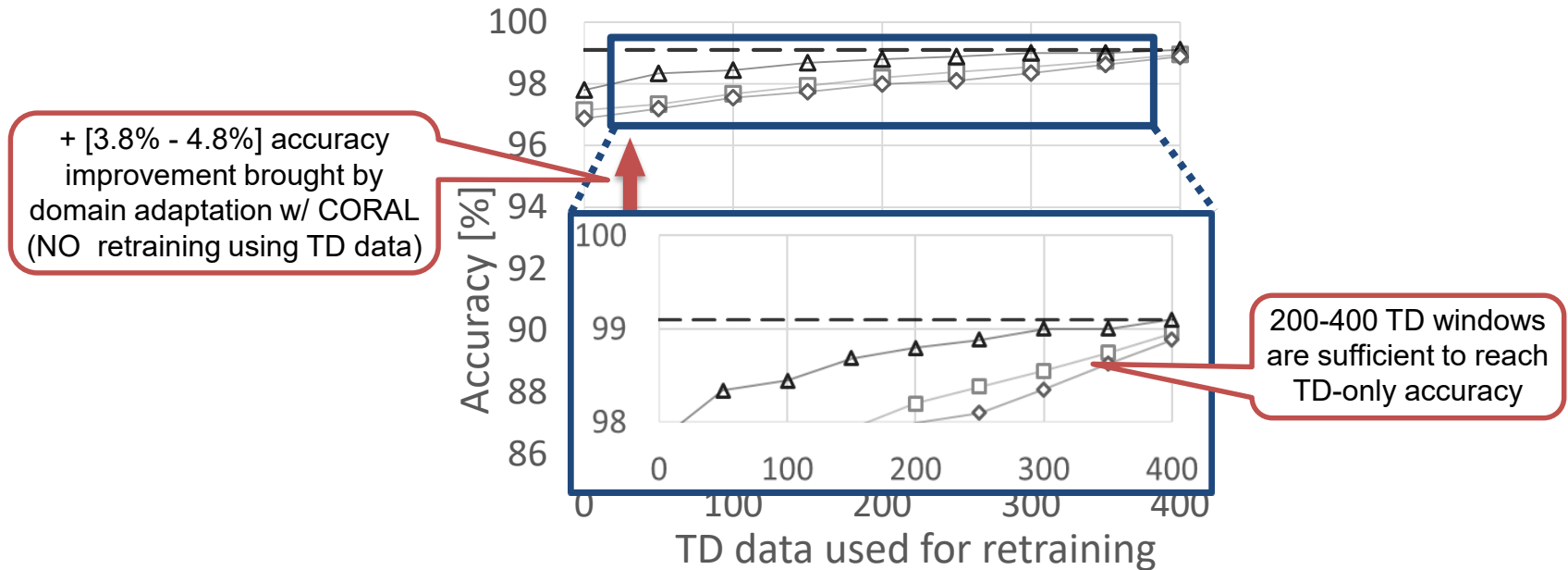
- trains the classifier only on source domain data ( $|SD|=5000$  windows), then test on the TD data
- equivalent to Pure Transfer Learning



# TL-assisted failure-cause identification: results

Window size = 20sec

SD=LP1 (1 hop) → TD=LP3 (3 hops)



—◇— SD 1000 samples    —□— SD 3000 samples    —△— SD 5000 samples    - - - TD only    — SD only

F. Musumeci *et al.*, "Transfer Learning across Different Lightpaths for Failure-Cause Identification in Optical Networks", *ECOC 2020*

