



POLITECNICO
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Workshop: AI on Optical Networks @BUPT

Emerging Research Directions for Machine Learning in Optical Networks

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What is Machine Learning?

- *“Field of study that gives computers the ability to learn without being explicitly programmed” (A. Samuel, 1959)*
- *“... through data observation”*
- For our purposes: An set of math/statistical **tools** to make predictions/decisions based on monitored data
...in the context of optical networks
- Confusing overlap with other terms: Artificial Intelligence, Deep Learning, Data Analytics, Data Mining, etc.



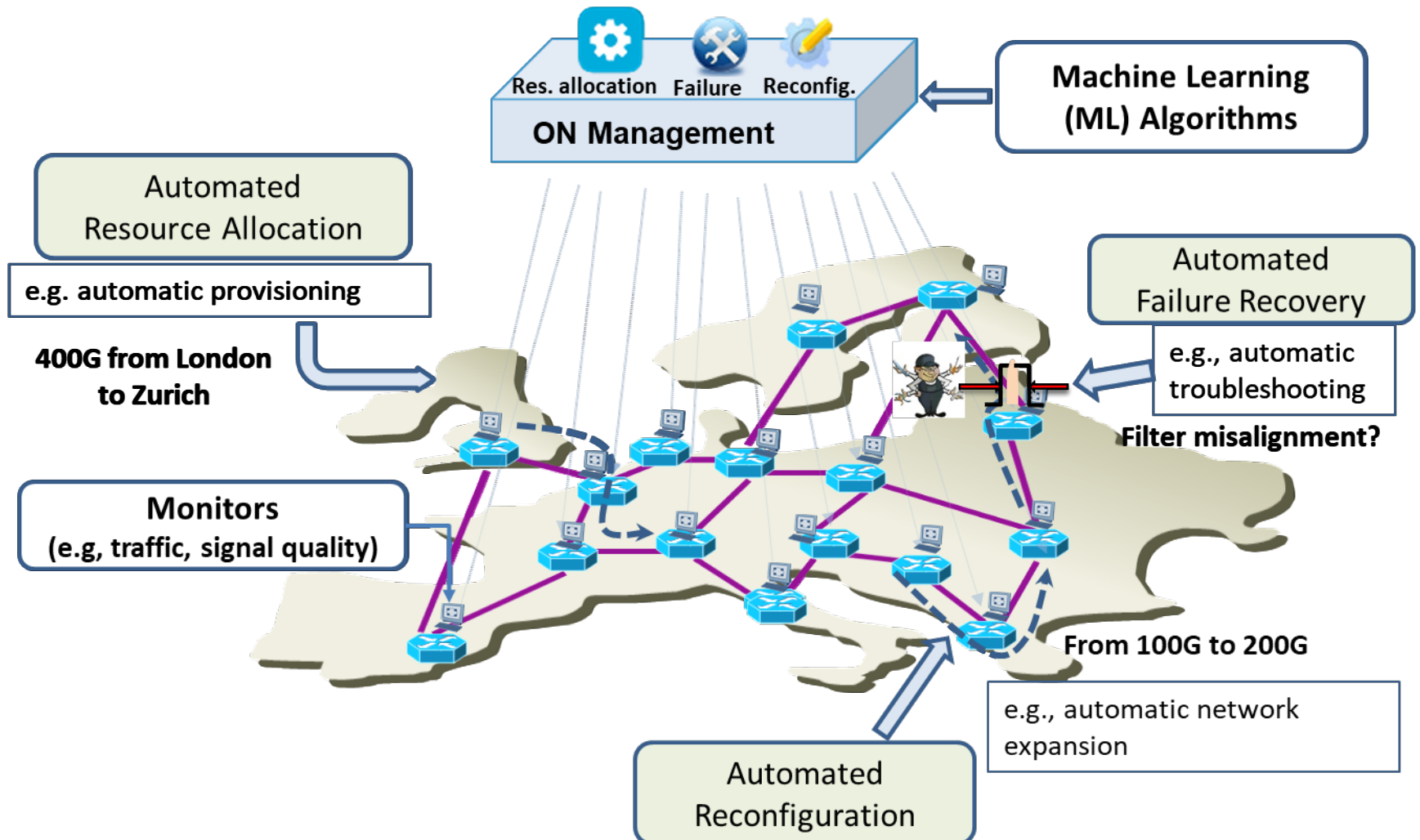
Why only now in optical networks?

- Dominating complexity
 - Coherent Transmission /Elastic Networks
 - Several system parameters: channel bandwidth, modulation formats, coding rates, symbol rates..
- Lack of skilled workforce
 - NTT warning (*OFC 2017*): aging population, increasing competition for young STEM workforce
- 5G Transport
- New enablers @ *Mngt&Cntr* plane
 - Software Defined Networking
 - Edge computing
 - OPM's (some are for free.. as in coherent receivers..)



Automation of Optical Network Management

- Management is still largely manual/human-based!



Covered topics

- QoT estimation and Routing and Spectrum Assianment
- Soft-Failure Mode Identification
- Quickly, some other applications...

I'll share my experience in developing ML-based solutions in Optical Networks



Motivation

Increasing «degrees of freedom»

- A wider range of **degrees of freedom** (parameters) is available to system engineers:
 - path
 - spectrum
 - modulation format
 - baud rate
 - FEC coding
 - single/multicarrier transmission
 - nonlinearity mitigation solution
 - adaptive channel spacing
 - ...
- Combinations of these lighpath parameters grow dramatically
- Possibly, for all of these combinations, we shall calculate a QoT



Existing (pre-deployment) estimation techniques for lightpath QoT

- **“Exact” analytical models** estimating physical layer impairments (e.g., split-step Fourier method...)
 - 😊 Accurate results
 - 😞 Heavy computational requirements
 - 😞 Not scalable to large networks and real time estimations
- **Marginated formulas** (Power Budget, Gaussian model...)
 - 😊 Faster and more scalable
 - 😞 Inaccurate, high margination, underutilization of network resources (up to extra 2 dB for design margins [1])

[1] Y. Pointurier, "Design of low-margin optical networks," in *IEEE/OSA Journal of Optical Communications and Networking*, vol. 9, no. 1, pp. A9-A17, Jan. 2017. doi: 10.1364/JOCN.9.0000A9

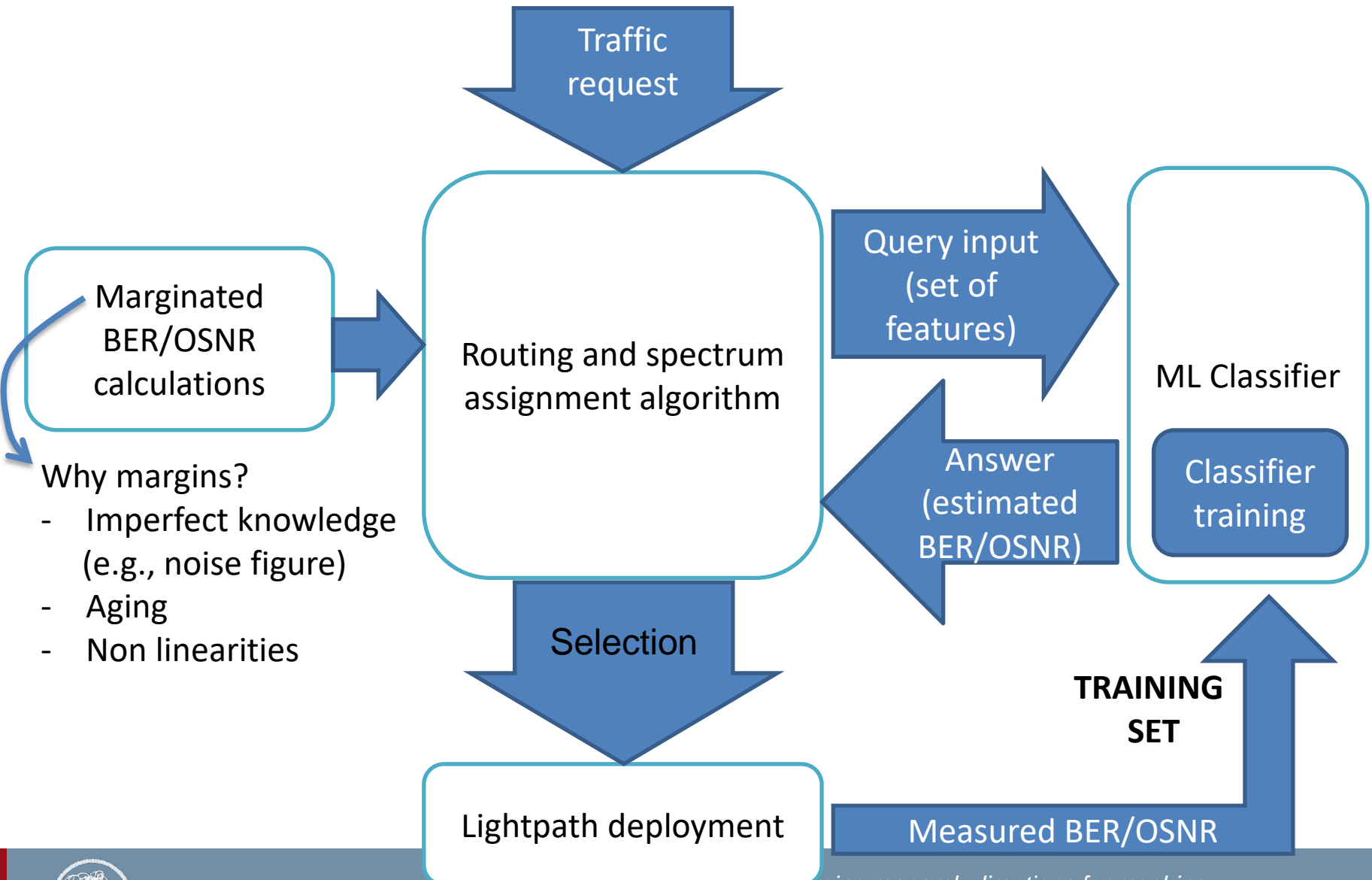


Machine Learning as an alternative approach?

- Machine Learning exploits knowledge extracted from field data...
 - QoT of already established lightpaths, e.g. using monitors at the receiver
 - to predict the QoT of unestablished lightpaths
-
- No need for complex analytical models
 - Fast and scalable
 - Requires training phase with historical data
 - 😊 How long must the training phase be?
 - 😊 How accurate will the estimation be?
 - 😞 Objectives of our numerical analysis....



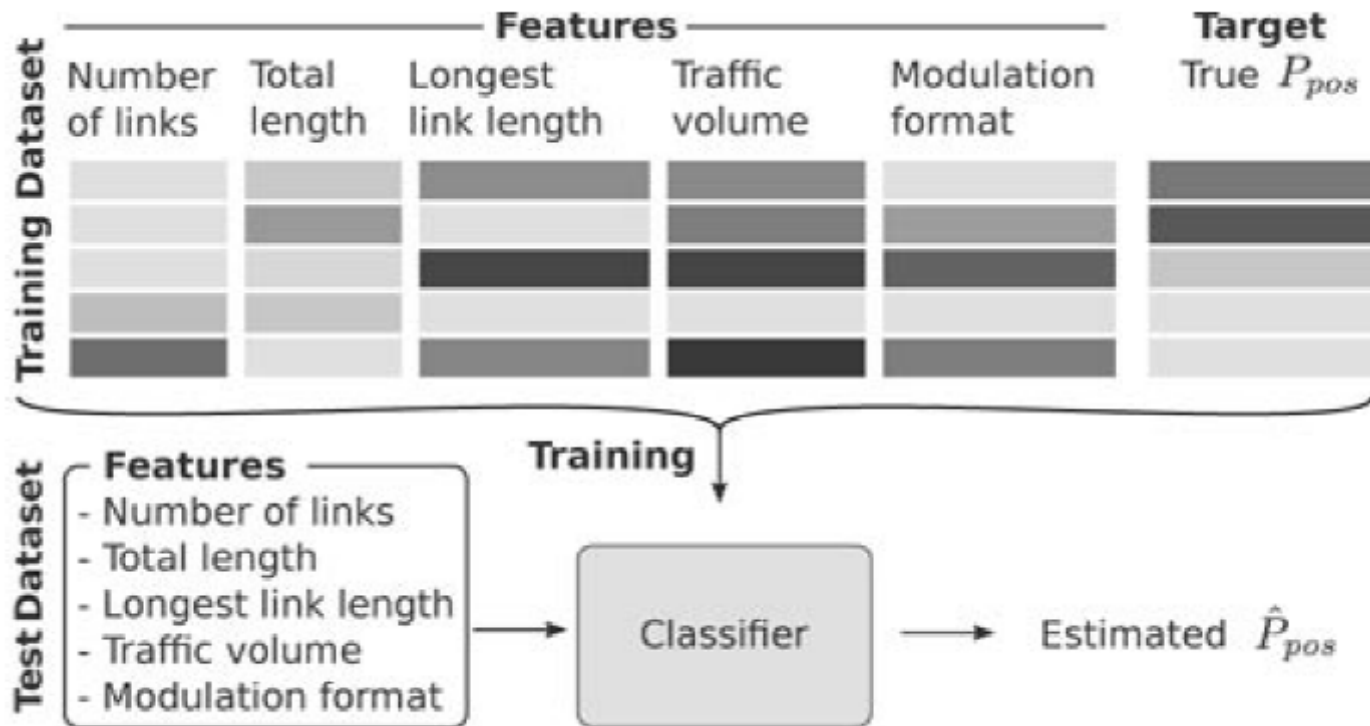
RSA interplays with QoT estimation



How does it work?

A possible implementation of ML-based QoT estimation

- Input: set of lightpath features
- Output: probability that $\text{BER} \leq T^*$



(Case of **local knowledge**, but we can add more features for **network knowledge**)

How our proposed ML classifier works

Case 2

- To the previous 6 feature we add, for the «most interfering left and right neighbors»:
 - guardband
 - traffic volume
 - modulation format
- (Case of **complete** knowledge)
- Note: these additional six features are chosen with the intent to capture cross-channel nonlinear effects



Which Machine Learning Technique?

- We use a Random Forest (RF) classifier with 25 estimators
- To take this choice, we have compared:
 - 5 RF classifiers
 - 3 k-Nearest-Neighbor classifiers

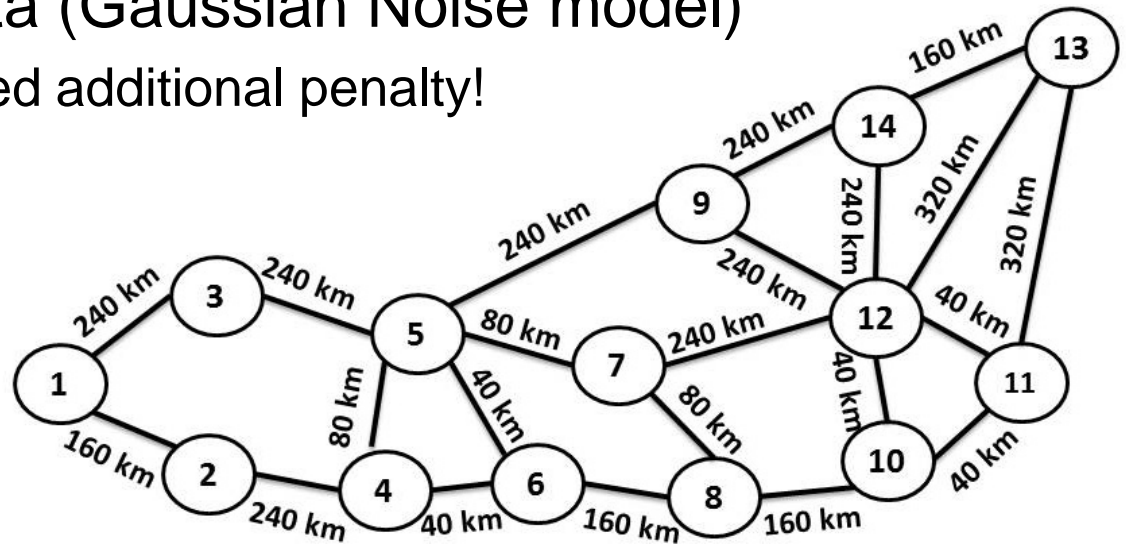
Algorithm	Training time (s)	Test time (s)	AUC	Accuracy
Dummy classifier	0.048979	3.83 e-07	0.501	0.539
1 Nearest Neighbor	1.183121	4.83 e-05	0.959	0.957
5 Nearest Neighbor	1.085116	5.05 e-05	0.991	0.965
25 Nearest Neighbor	1.211694	6.91 e-05	0.996	0.965
Random Forest 1 tree	0.076944	3.96 e-07	0.991	0.965
Random Forest 5 trees	0.180835	6.24 e-07	0.995	0.970
Random Forest 25 trees	0.721042	1.56 e-06	0.996	0.968
Random Forest 100 trees	2.830545	5.32 e-06	0.996	0.966
Random Forest 500 trees	14.052182	2.63 e-05	0.996	0.966

- RF with 25 estimators provided the best trade-off between performance and computational time

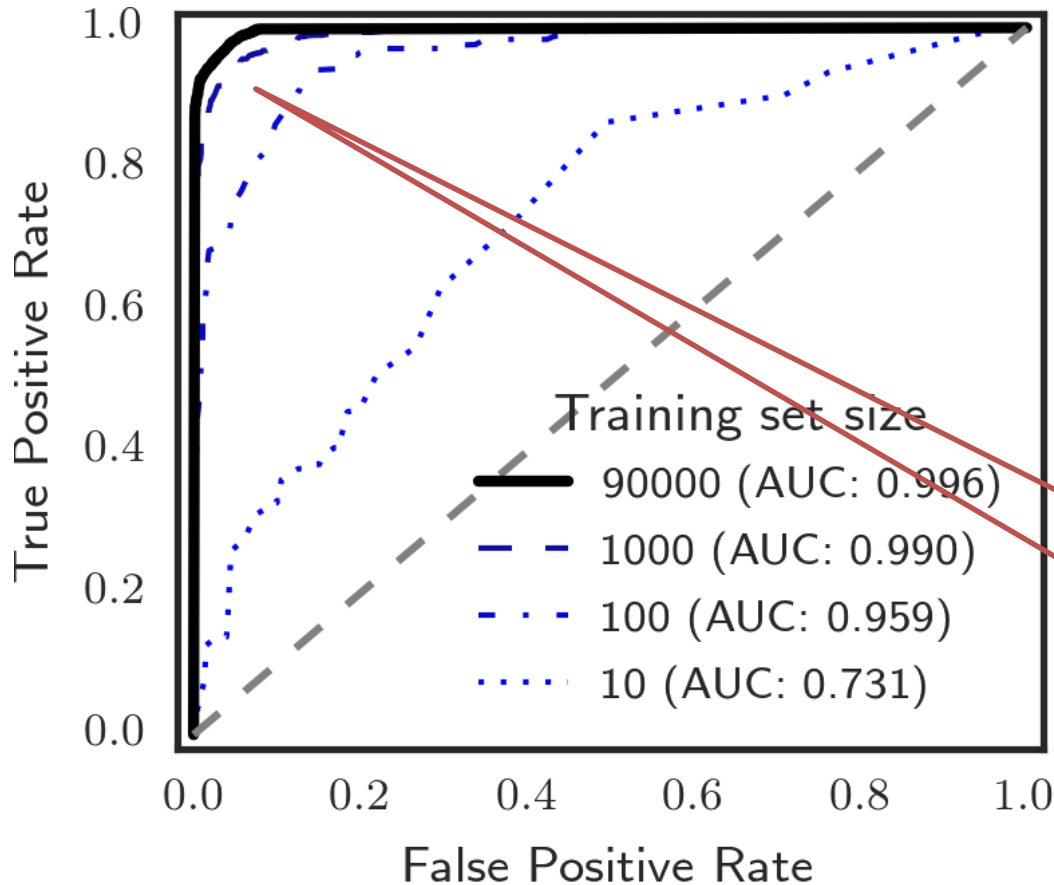


Training and Testing Scenario

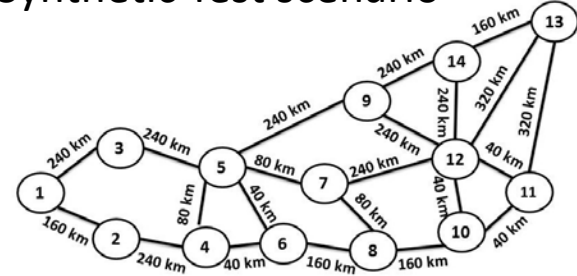
- Japanese optical network
- Flexgrid @ 12.5 GHz slices
- Transceivers @ 28 GBaud with adaptive modulation formats
 - DP-BPSK, -QPSK, -8-QAM, -16-QAM, -32-QAM, -64-QAM
- Traffic requests: [50;1000] Gbps
- Synthetic training data (Gaussian Noise model)
 - With expneg distributed additional penalty!



How big shall training dataset be?



- Synthetic Test scenario



- Accuracy: Area under the ROC curve (AUC)

Take-Away 1: Training phase has a reasonable duration

C. Rottondi, L. Barletta, A. Giusti and M. Tornatore, *A Machine Learning Method for Quality of Transmission Estimation of Unestablished Lightpaths*, JOCN2018



How to build the training dataset?

- Use historical data
 - ☹️ We will never observe samples of with too high BER!!
- Use random probes:
 - ☹️ Very costly (high spectrum occupation)
- Use selective probes:
 - 😊 Lower spectrum occupation, good accuracy

TABLE V: AUC comparison of probing approaches

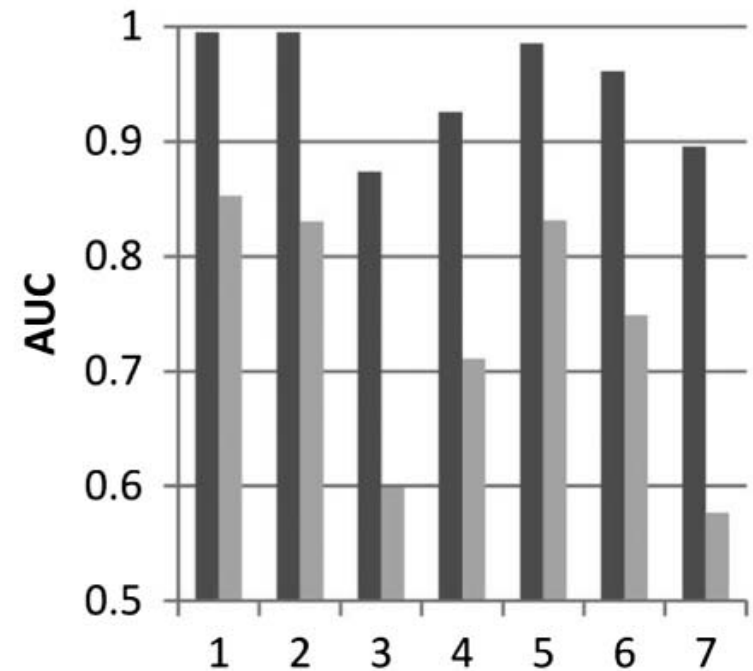
Training set	AUC (full testing dataset)
C (historical)	0.77
C (selective, 5% probes)	0.85
C (selective, 10% probes)	0.87
C (selective, 25% probes)	0.89
C (selective, 50% probes)	0.89
A (random)	0.98

Analysis of feature relevance

- Removing irrelevant «ML-input features» makes the system less costly and less complex to manage

TABLE IV: The considered feature subsets

	S1	S2	S3	S4	S5	S6	S7
number of links	✓	✓	✓	✓			
hightpath length	✓	✓	✓	✓	✓	✓	
length of longest link	✓	✓	✓	✓			
traffic volume	✓	✓	✓		✓		✓
modulation format	✓	✓		✓	✓	✓	✓
guardband, modulation format and traffic volume of nearest left and right neighbor	✓						



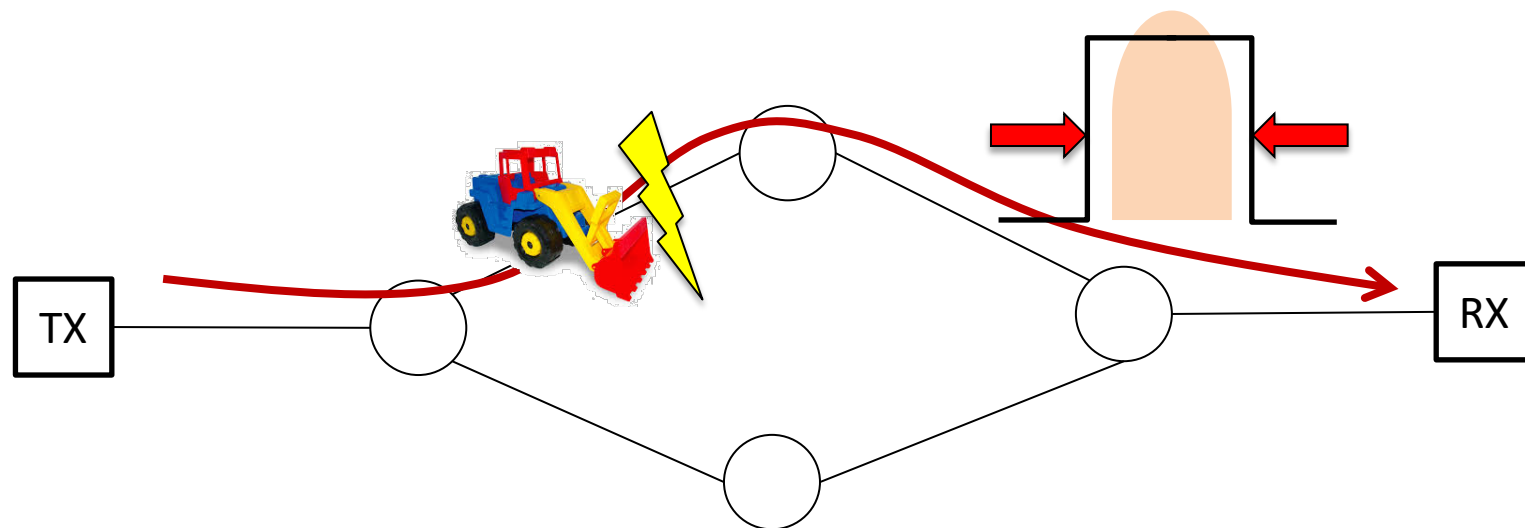
Covered topics

- QoS estimation and Routing and Spectrum Assignment
- **Soft-Failure Mode Identification**
- Quickly, some other applications...



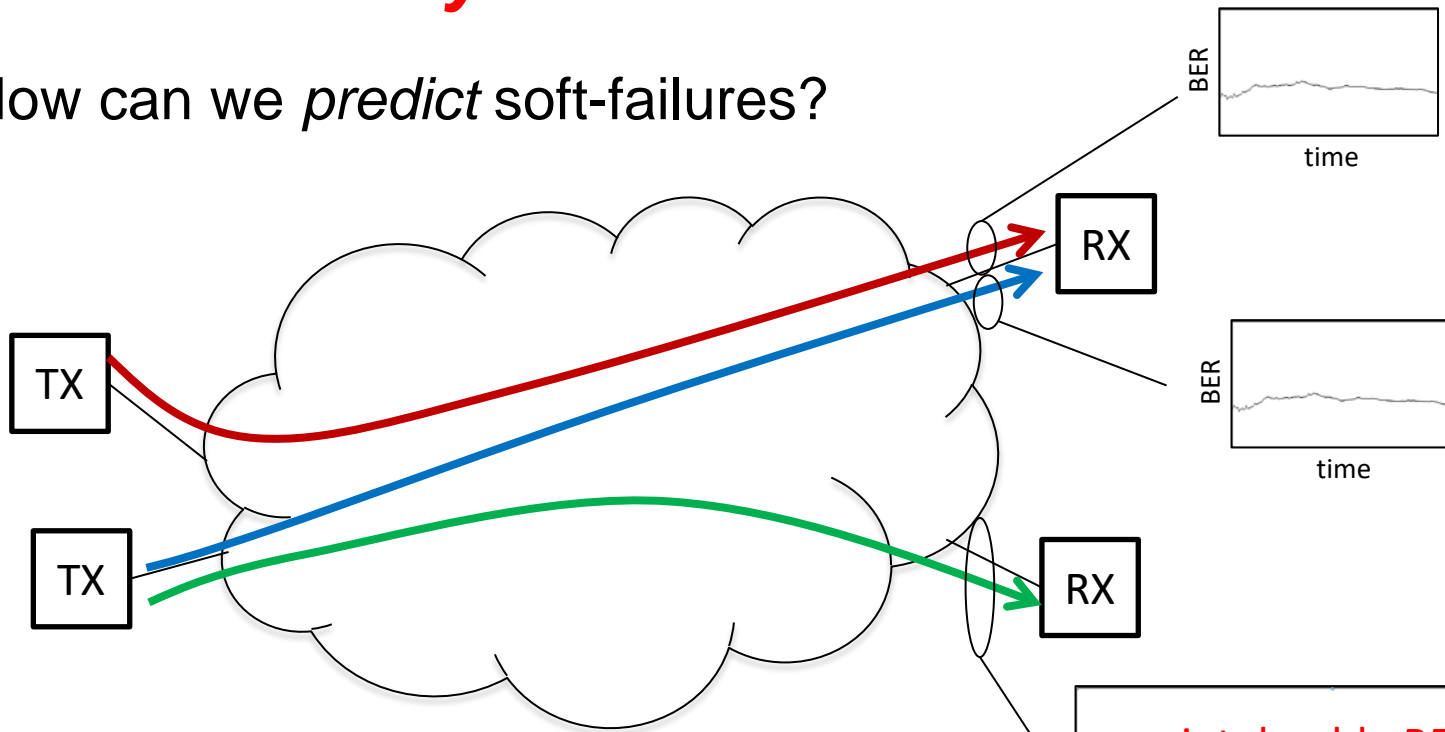
Two main failure types in optical networks

- 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*)



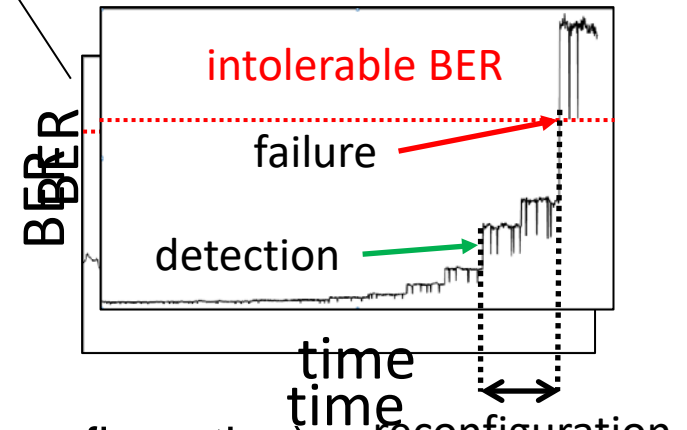
Soft-failure *early detection*

- How can we *predict* soft-failures?



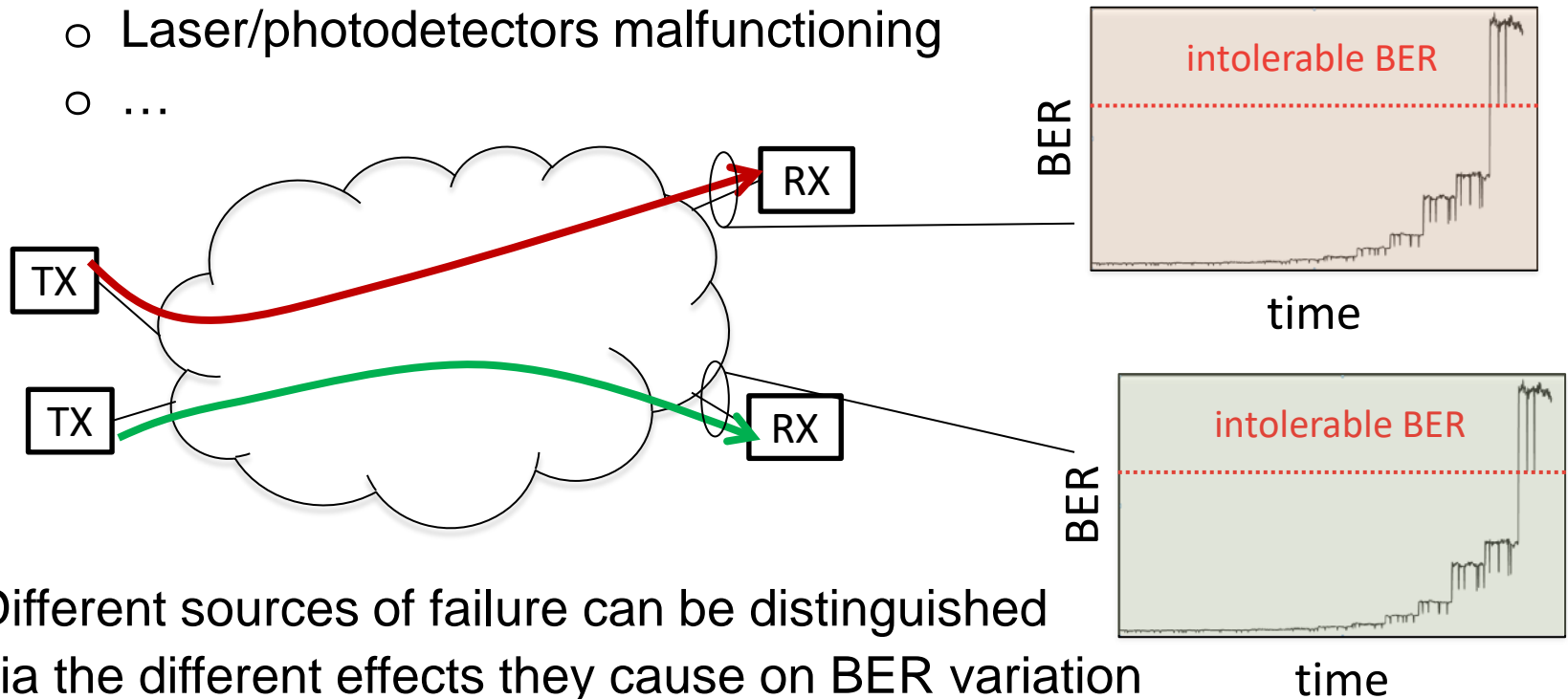
Perform continuous monitoring of Bit Error Rate (BER) at the receiver...
... until some “anomalies” are detected

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



Soft-failure *mode identification*

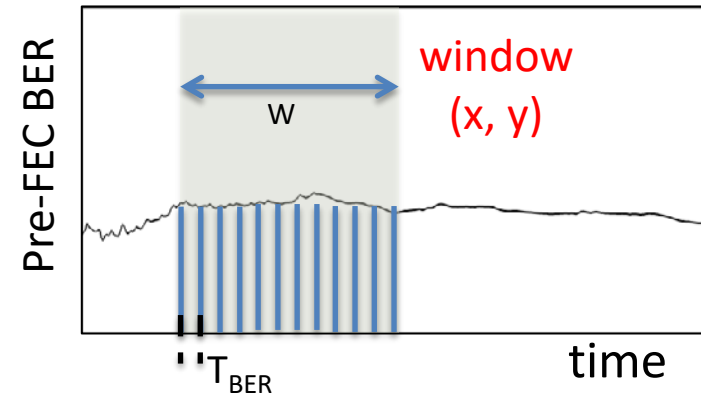
- How can we identify the *mode* of the failure?
 - Failures can be caused by different sources
 - Filters shrinking/misalignment
 - Excessive attenuation (e.g., due to amplifier malfunctioning)
 - Laser/photodetectors malfunctioning
 - ...



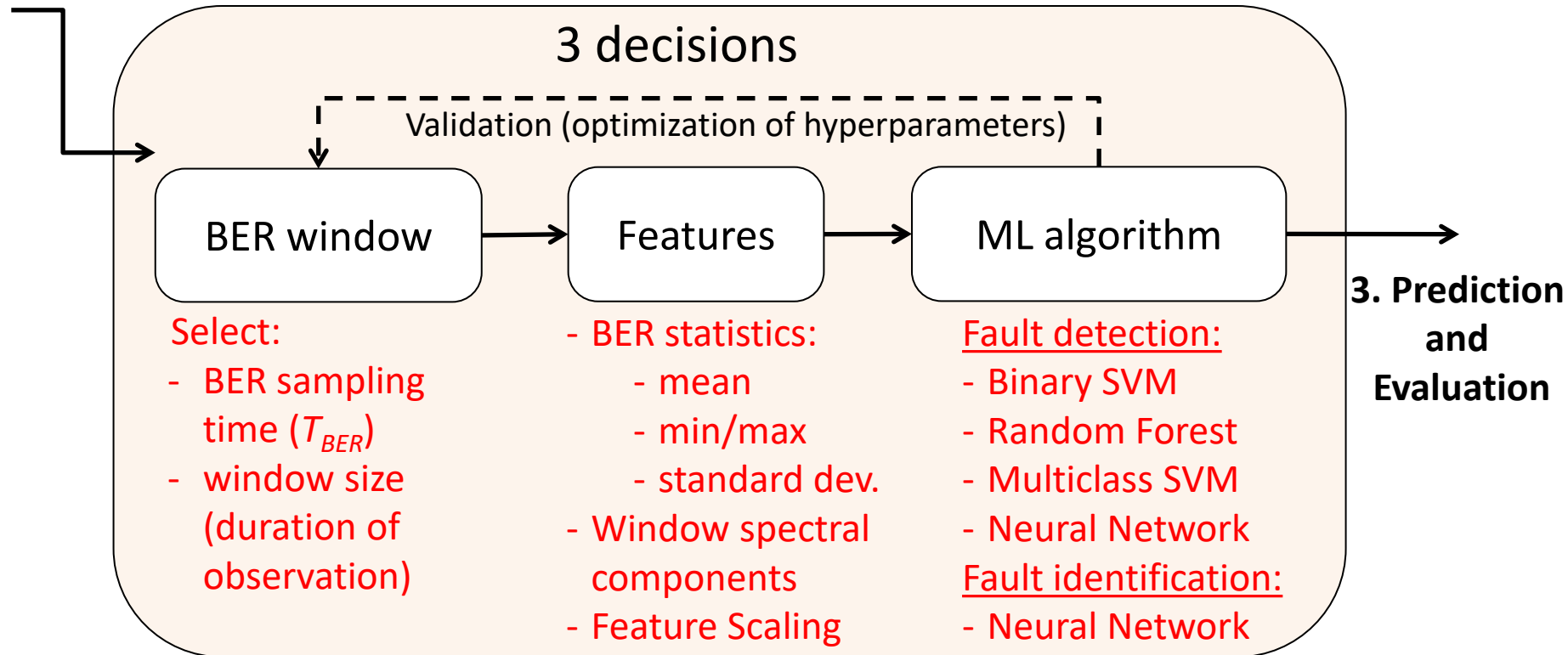
Different sources of failure can be distinguished via the different effects they cause on BER variation (i.e., via different BER “features”)

2nd Phase of our study

Deciding ML algorithm, Training & Validation

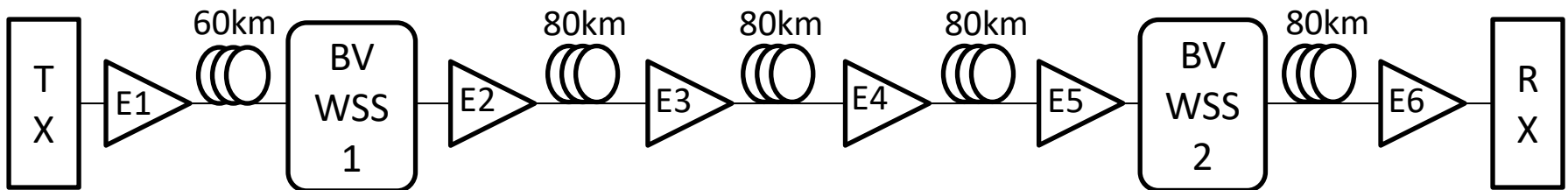


1. Data Retrieval



Testbed setup

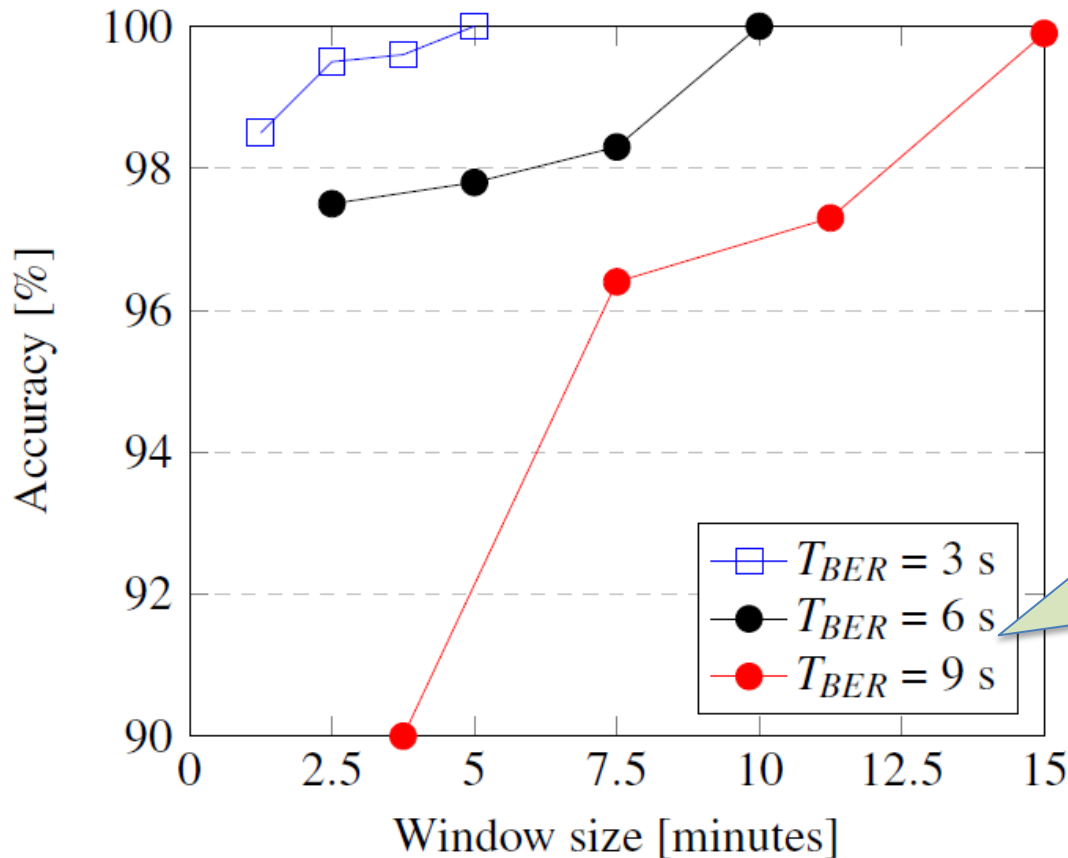
- Testbed for real BER traces
 - Ericsson 380 km transmission system
 - 24 hours BER monitoring
 - 3 seconds sampling interval
 - PM-QPSK modulation @ 100Gb/s
 - 6 Erbium Doped Fiber Amplifiers (EDFA) followed by Variable Optical Attenuators (VOAs)
 - Bandwidth-Variable Wavelength Selective Switch (BV-WSS)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



Numerical results: *Identification*

Accuracy vs window features

- Neural Network



Take-away 3: To perform failure-cause identification, fine sampling period of BER is needed



Benefits for operators

- Reduced Time To Repair (TTR)
 - Almost instantaneous troubleshooting
 - TTR from hours/days to minutes/hours?
- Reduced Service Downtime
 - Early detection eliminates a class of failure

- First demonstrations

Vela et al., “BER degradation Detection and Failure Identification in Elastic Optical Networks”, in Journal of Lightwave Technology, vol. 35, no. 21, pp. 4595-4604, Nov. 2017

S. Shahkarami, F. Musumeci, F. Cugini, M. Tornatore, “Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks,” in Proceedings, OFC 2018, San Diego (CA), Usa, Mar. 11-15, 2018



Many open questions/challenges!

- **[QoT]** Optical network is a living network
 - Continuous training.. How?
- **[QoT]** How to build the right training set?
 - Rare occurrences of false positives -> Low accuracy...
 - Selective probes?
- **[Failure]** What if completely new/unclassified failure arise?
 - «Novelty detection» ?



Overview of other applications

- **Physical layer**
 1. Optical amplifier control
 2. Modulation format recognition
 3. Nonlinearities mitigation

- **Network layer**
 1. Traffic prediction and virtual topology design
 2. Flow classification

Classification taken from: F. Musumeci et al., "A Survey on Application of Machine Learning Techniques in Optical Networks", Accepted to IEEE Communication Surveys and Tutorial, available online (Arxiv)



Thanks for your attention!

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