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A seafarers tale: Real-time Ship Monitoring

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- One of the largest, independent owners of modern large-size container-ships.
- A proven track record of operational excellence and technological leadership.
- Our distinct edge in advanced shipping technology and long track record of
 - safety,
 - efficiency and
 - environmental responsibility,
- Helped us forge lasting relationships with our customers
- Our deep understanding of the shipping dc  us to get involved quite early (1980s) into software for shipping as well.

Real-Time Ship Management Objectives

Fuel Consumption
Tracking



Hull Drag
Optimisation

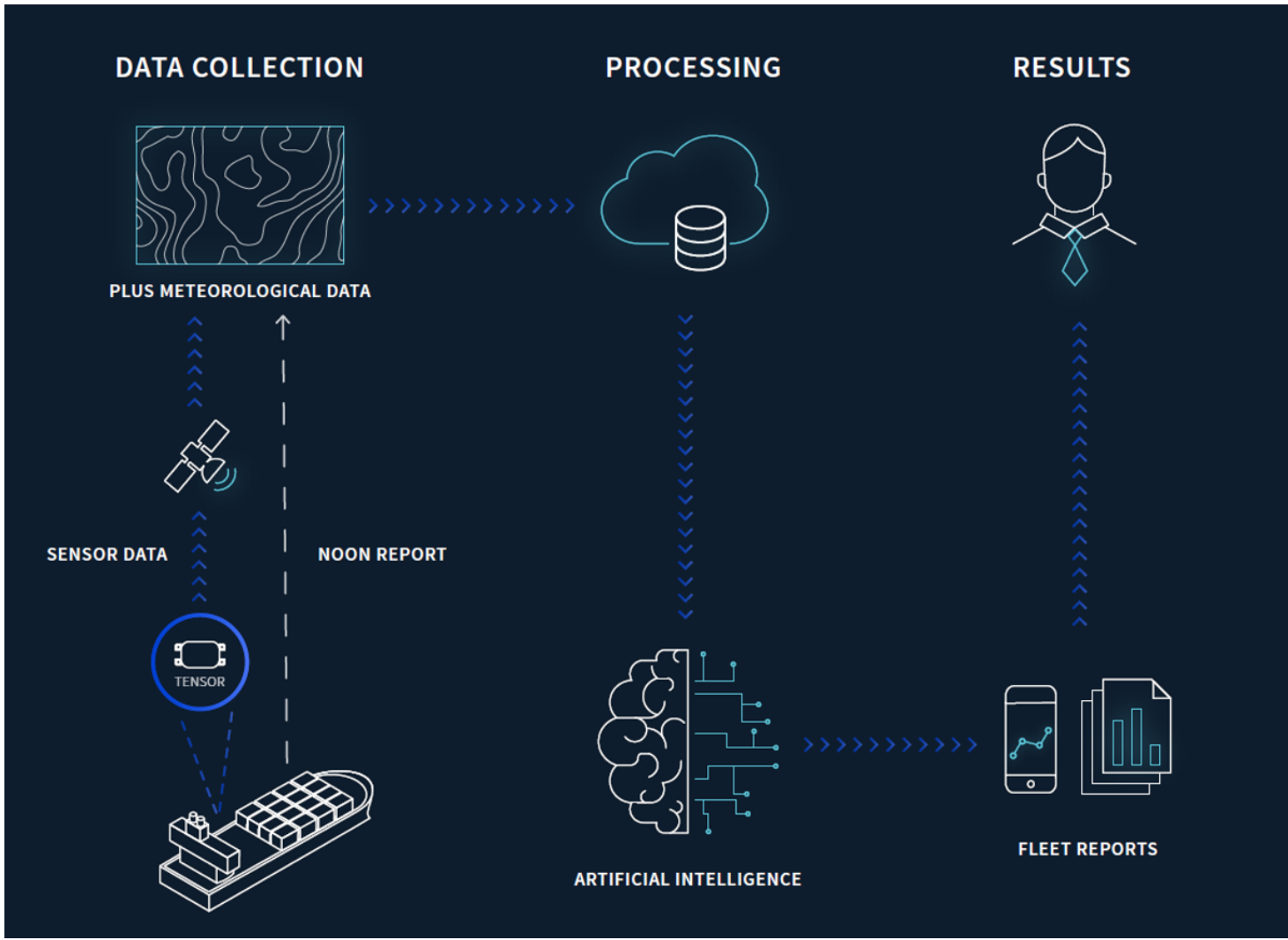


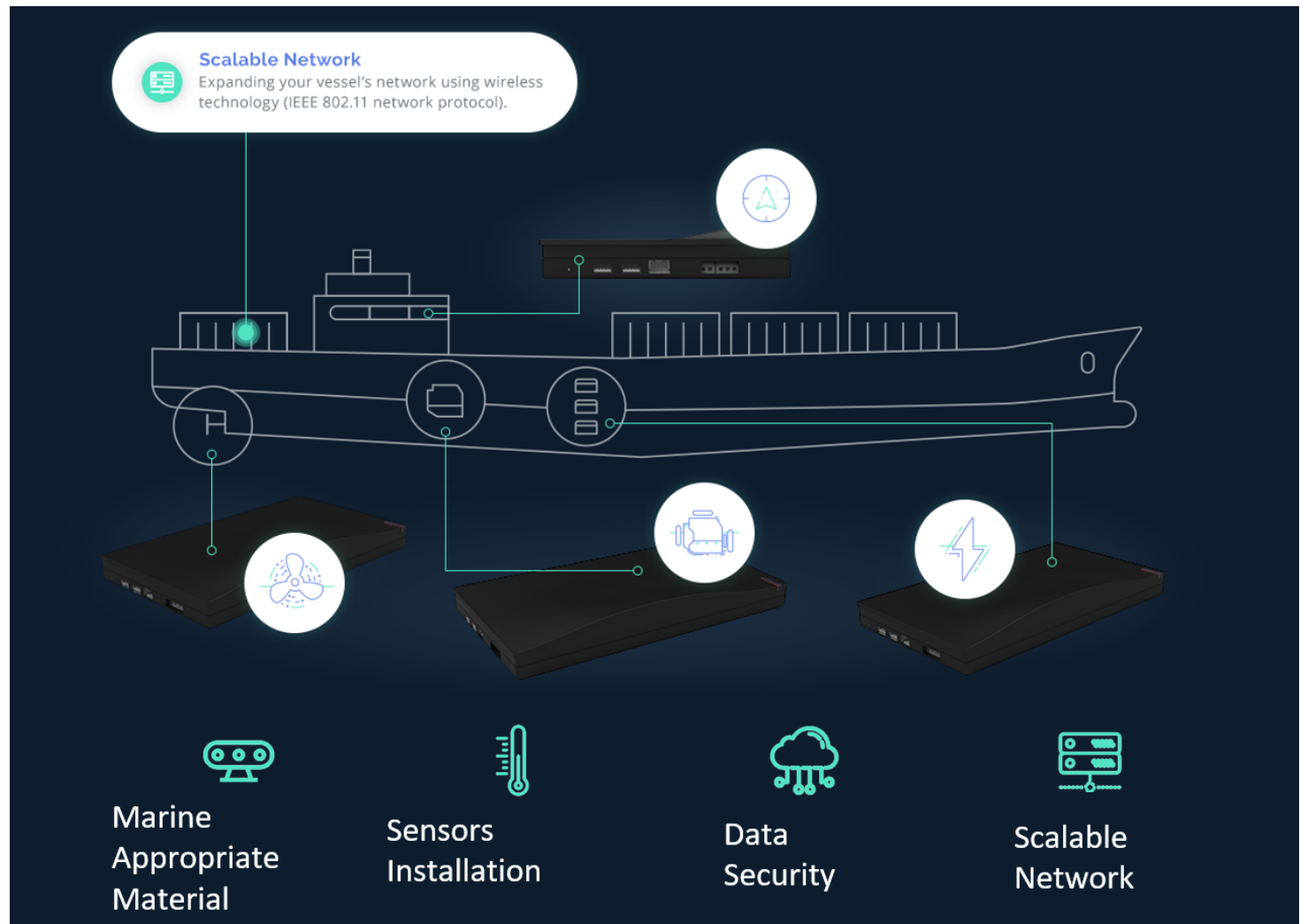
Machinery
Troubleshooting



Environmental
Compliance







- Simple data logging is not a solution anymore
- Ignorance and over-information are the two sides of the same coin
- Actionable Information is required from the end-user
- Analytics over big data is mandatory

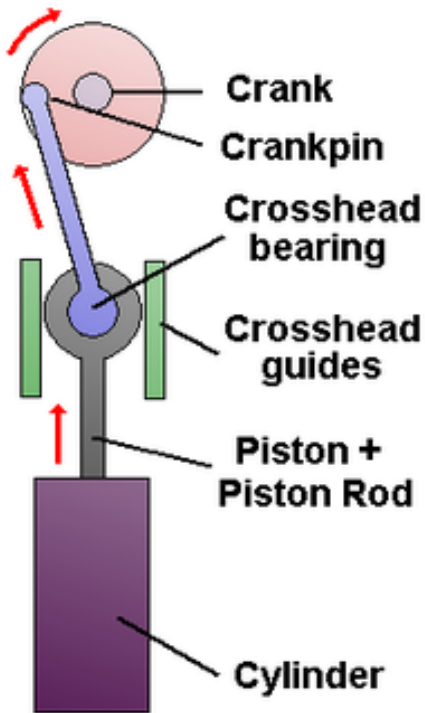


- Vessels have time-constrained routes
- When a main engine part fails unexpectedly
 - The vessel may go off-hire
 - Chartering revenues decrease
 - Urgent part replacement increases cost
 - Bad company image
- Finding potential failures allows
 - Timely ordering of spare parts
 - Replacement of parts before failure



- Main-engine malfunctions is a vast problem
- We focus on Cross-head Bearings malfunctions
 - Evolve gradually
 - Can only be detected with on-board inspection
 - No known correlation of metrics to predict it
- Slow Steaming
 - Common practice imposed by charterers
 - Used to save fuel but
 - Causes bad lubrication of the cylinder
- We wish to predict these breakages
- This physical phenomenon is hidden in the data






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The economics of slow steaming



Slow steaming is no longer a new concept to shipping. The practice of deliberately slowing down the speed of a ship is in fact a common operating feature of today's shipping market as a way to lower costs by reducing fuel consumption. And with shipping lines trying to stay profitable in the present weak freight market, slow steaming has proven a good way to trim operating expenditures so as to boost the bottomline.



■ Technical Challenges

- Many parameters are related to the malfunction
- Difficult to accurately predict failures
- Data-loss may occur (due to broken sensors onboard)
- Malfunction pattern identification seems to be data intensive and computationally demanding



■ Operational Challenges

■ Premature Alarms

- Increase the operating costs
- Cause ordering of unnecessary parts

■ Part replacement price depends on

- Where?
- When?
- Who?



- Operational Data: Telegrams

- 47K records
- Every 12 hours or upon arrival/departure
- Updated when an error is identified (rarely)

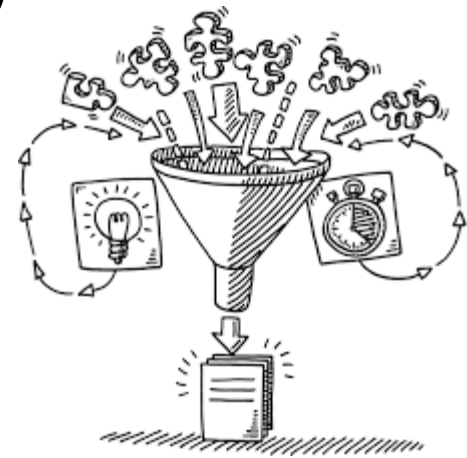
- General-purpose sensor data

- 21 different sensors
- 64M records
- Per-minute basis

- Main Engine sensor data

- 100 different sensors
- 64M records
- Per-minute basis

- Given our customer contracts, we expect a big rise in the number of monitored vessel, thus, this volume will increase dramatically.



- Real-time stream processing by distributed **CEP** to identify
 - Sensor malfunctions
 - Business rules violations
- **Preventive maintenance**
 - Taps on the **Data Quality Assessment** service
 - Efficient
 - Considers all available data-sets by the deployment configurations
- **Seamless Data movement and Data Analytics** to handle data sets distributed both at LXS and Object Store
- Enhanced SQL query performance against (even remote) Object Stores made possible by the **data-s technologies**



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Thank you!

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Data Quality Assessment Tool

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7

- A data quality assessment component

2

- Performs domain-agnostic, probabilistic error detection

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1

- Following a supervised learning approach

9

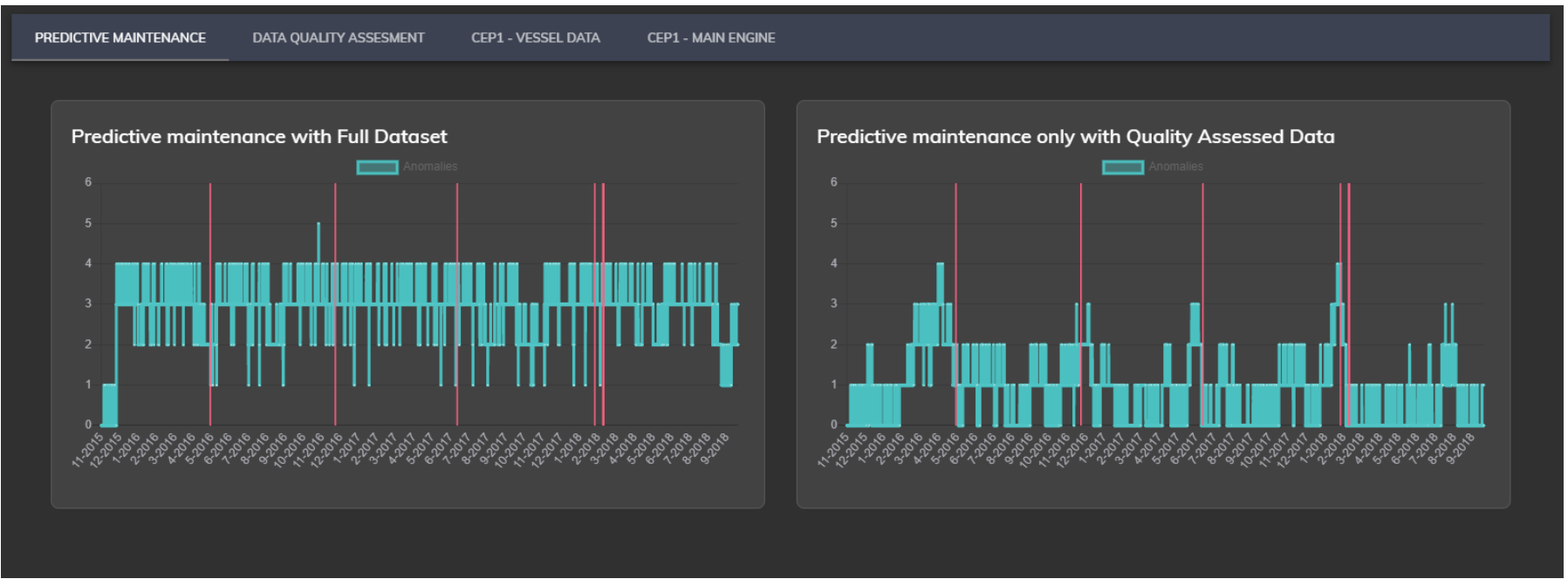
- Deep neural networks as a likelihood model

- Given a data set , compute a model

- Output: A probability for each record that is valid



Predictive Maintenance and Data Quality Assessment



- Combination of different algorithms
 - Supervised Learning
 - Semi-supervised Learning
 - Unsupervised Learning
- XC Boost
 - Labeled data with a static window of 30 days prior to defect
- One-Class Support Vector Machine (SVM)
 - Trained on data with no history of defects
- Multivariate Long short-term memory (LSTM)
 - Trained on data with no history of defects
- Rolling Weighted Permutation Entropy
 - Higher values of entropy (more information) indicates abnormal operation

