Summary of main outcomes of Panel discussion:

"Deep learning (DL) for PHM: Opportunities and Challenges" (P.Dersin,Alstom; O.Fink, ETH-Zürich)

May 3d, 2019,' Prognostics & System Health Management Conference', Paris

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Main opportunities of DL for PHM Applications:

- Ability for automatic feature learning substituting the need of engineering handcrafted features . This is particularly relevant in domains with high-dimensional, structured data, such as time series and images, where also deep learning has had its main successes so far.
- While previously the difficulty and the expert knowledge was mainly in feature engineering, the difficulty now transferred into finding the right network architecture for the specific problem.
- Ability to solve high-dimensional, complex problems with heterogeneous condition monitoring data.
- Ability to apply transfer learning to transfer the knowledge between different operating conditions or individual assets within entire fleet.
- Many advanced and powerful algorithms are available and are constantly developed further by the researchers. The majority of deep learning algorithms, however, are predominantly applicable to images. Particularly pre-trained DL architectures (with a defined number and types of layers, number of channels, size of convolutions, types of activation functions, etc.) such as AlexNet, ResNet-50, are only applicable to images or image-like inputs. Although also algorithms applicable to time series are available, the majority of recurrent algorithms are not as advanced as those applied to images.
- DL provides a huge community, constantly developing algorithms further with the potential to transfer the algorithms developed for computer vision and image processing to PHM applications.
- The available development platforms for DL are open source and provide an easily understandable and easy to use environment (e.g. Tensorflow, Pytorch).
- The advancements in text mining, natural language processing can be directly applied to maintenance reports and provide a benefit there.
- Enable optimization for decision making concepts never seen before for heavy industries.
- Abundance of data for perception on dynamic environment available.

    - *Many large organizations undoubtedly have an abundance of data that they may use internally.*
- : The vast majority of DL papers are accessible open source.
- DL may enable/help introduction of new sensors and sensing technology.

Main challenges of DL for PHM Applications:

Apart from the need for orders of magnitude more labelled data, most of the challenges listed below are not *deep* learning specific .Maybe we should look at how these problems were tackled during the last wave of enthusiasm for Neural Networks /learning research back in the 90s?

- DL algorithms require large representative datasets (in the ideal case with labels, however, labels are typically only scarcely available in PHM applications).
- Due to the lack of labels, the learning problems in the field of PHM need to be defined as unsupervised (or semi-supervised, if data is labeled partially) learning problems. While supervised learning is broadly established, unsupervised learning is an evolving field of research.
- Models deployed to real-time predictive analysis and automatic decision making or decision support for important or safety critical decisions require a high maturity of IT implementation and particularly cyber-security .
    - You need robustness to unseen data, malevolent data, adversarial attacks, etc.
- Developed algorithms highly depend on the representativeness of the training datasets: refurbishment and overhaul may change data characteristics and therefore require the algorithms to be adapted or retrained.
    - In the aerospace industry, one would talk more about evolution of the design during operations of a fleet (retrofitting). Maintenance operations, overhaul should be taken into account (automatically detected or deduced from maintenance logs/systems).
- Lack of understanding by the domain experts often results in lack of trust and requires therefore elaborated decision support and trust building tools.
    - False alarm is a poison for building trust of operators.
- Challenge to develop "Explainable AI": e.g. by making the features explainable or making it better understandable which impact changes in the input have on the output and how the output can be interpreted.
- There is need to change the organizational culture towards new AI: the challenge here is to bring together engineers working with traditional physics-based approaches and data scientists.
- Lack of benchmark datasets for PHM applications (e.g. CMAPSS dataset is highly overused and is already around 10 years old).
    - Benchmarks in images are not a lot either and are also old. Difficulty for PHM is having run-to-failures datasets on a sufficiently important number of assets to have a representative problem.
- Creating algorithms across companies' borders requires sharing the data across companies' borders (particularly between OEMs and operators), which has been a major obstacle also in the past.
    - Two blockers:
        - the value chain (who gains what?) If this is not settled, collaborations between data/expertise owners will be difficult).

        - Privacy of data (look for privacy by design, differential privacy).
- The main focus of the DL community is on computer vision and NLP, not that many architectures dedicated to complex physical systems.
- Incorporate engineering knowledge in DL (Neural ODE e.g.)
- Challenge to establish systems engineering verification, validation and integration.
- Risk of focusing mostly on end-to-end concept and ignoring industrial robustness.
- Representational power vs model building tractability tradeoff is still complicated for cyber-physical systems.
- ML mostly provides a static mapping, however complex industrial systems require the integration of dynamics.
- Quantifying uncertainty of the developed methods is still a challenge and there are no established approaches to uncertainty quantification in the data-driven PHM community (while uncertainty quantification for physics-based approaches has become state of the art with a set of approaches widely accepted by the community).

Potential application domains of Deep Learning within PHM

- The opinion has been voiced that Deep Learning could be particularly useful for complex systems, with high-dimensional and heterogeneous condition monitoring data having complex relationships between the signals.However, this assertion has been challenged by some panelists, arguing that DL so far has been mostly successful with *structured* data (except for texts, which can be considered as unstructured data, and for which deep learning has been quite successful).
- However, first test shallow and simple architectures: if they solve the problem, there is no need to apply any more complex DL architectures.
    - Use DL only when standard ML fails.
- DL particularly useful when data can be transformed to 2D images.
    - That is a subject to be studied. How can PHM data be transformed into images?
- Large benefits in applying NLP to maintenance reports for different purposes.
    - Yes, but you need to train NLP models specifically for your application. Off-the-shelf NLP models are not good for industrial applications where the vocabulary, abbreviations are very different than standard language.

Roles of the various stakeholders: OEMs, operators, large companies, SMEs, start-ups in Deep Learning for PHM

- While OEMs control the physics-based models, it is typically the operators that have access to large amounts of data, collaboration between operators and OEMs can bring benefits for both stakeholders. However, this requires a tangible business model or agreement. It has been difficult so far to design such business models that are built upon sharing the benefits (among others because it is difficult to quantify the benefits directly and also the incremental increase of the benefits with some partial data of model contribution).
- There are different approaches to this challenge in different industries but even within the same industry: e.g. establishing platforms where either data or the developed models are shared.
    - *Skywise is a good example*
- Startups have been popping up in the field of PHM solely relying on developing models based on condition monitoring data (without access to the physical models or understanding the

systems). So far, only few have been successful with their business models. OEMs are largely relying on their system knowledge.

  - How can DL help bridging the gap between physical models and data-based models?

Roles of universities in the context of the "DL revolution":

- Educating young talents that are combing engineering knowledge and data science capabilities; but that are also able to think critically.
- Working on the unsolved challenges in DL, particularly applied to PHM problems, and collaborating more with industrial partners (proactivity to establish such collaborations should be coming from both directions).

Unsolved problems / open research questions in the PHM DL:

- Assessment of algorithms stability/robustness.
- How to extract 'knowledge' from experts (and thus address knowledge management issues, with scarce domain experts retiring, etc.) and develop decision support systems based on the extracted knowledge.
- How to extract knowledge from the huge documentation produced during design?
- Certification issues when DL algorithms are applied to safety critical systems: the safety implications of predictive maintenance.
  - That would mean switching to predictive maintenance as the standard maintenance policy for parts of the systems, so need of certification. What should we demonstrate to regulatory authorities so we all trust the detections, predictions of the algorithms?
- Efficient ways to select /optimize the architecture / hyperparameters of the neural networks (i.e. how many layers, etc.)
  - That is a huge problem because it is very costly to assess the efficiency of a configuration.
- Providing statistical guarantees for DL algorithms.

What can we do as society of PHM experts to better benefit from the vast amounts of condition monitoring data?

- Since ImageNet [1]was what has driven DL in computer vision, we should create datasets that can be used by the community /researchers. Labelling the ImageNet data required little more than average human intelligence and hence could be crowdsourced. The difficulty faced in PHM however is the willingness of the companies to share their datasets. Currently, many companies are still reluctant to openly share their PHM datasets. Crowdsourcing the labeling of PHM datasets will not be applicable. Since most of the data in PHM is unlabeled, it would be mostly for unsupervised learning (contrary to the ImageNet that is fully labeled).

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[1] A database designed for object recognition in mages containing more than 14 million labeled images with 20,000 categories. The database is considered to be one of the drivers of DL progress. A challenge based on the dataset (ImageNet Large Scale Visual Recognition Challenge (ILSVRC)) has meanwhile led to results overachieving human performance. The first breakthrough of DL is considered to be the application of AlexNet to ImageNet in 2012, which has led to a top-5 error of 15.3%, a significant drop compared to other previous winners with architectures based on feature engineering.

- Establish a culture of sharing between different stakeholders :data, algorithms, but also negative outcomes (things that don't work, to save resources).
- Datasets that are currently used as benchmarks (e.g. CMAPSS) are old (10 years) and are overused; the operators should be using some of their data and partner with some researchers who could improve the algorithms.The way to go could be that the companies ask the researchers to apply their best algorithms on their datasets and based on that, the collaboration could improve.
- Close the gap between industry and academia: inspire researchers to work on problems that are meaningful and will have an impact on the industry.