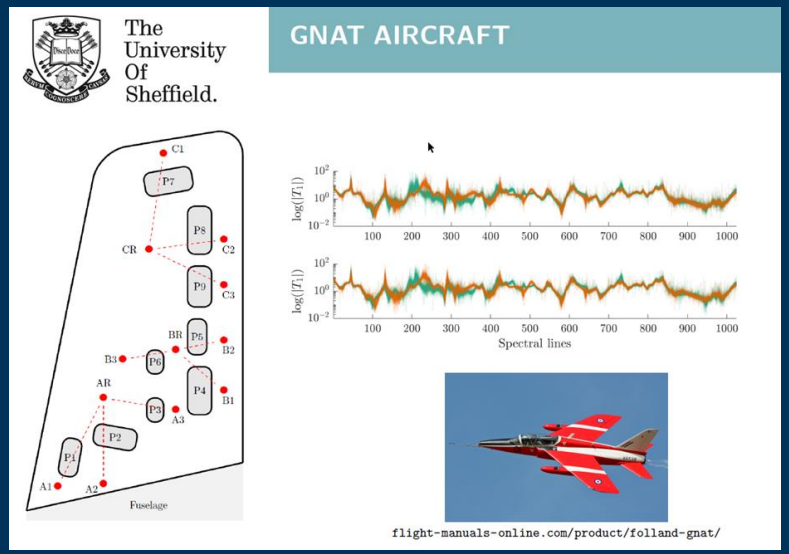
HBM Prenscia Technology Day

Virtual Seminar Series



Overcoming Information Sparsity in Engineering Datasets - A Transfer Learning Viewpoint

Presented by Dr. Paul Gardner
Research Associate, Dynamics Research Group
University of Sheffield

Session #5: Mathematical Modelling for Data Analytics, Durability, and Reliability #1

Overcoming Information Sparsity in Engineering Datasets - A Transfer Learning Viewpoint

Abstract

In the age of big data many engineering companies are collecting large quantities of data from their systems in operation. However, much of this data represents normal, benign, operating conditions, and reveals little information about what data will look like when my system is damaged, or what will the system response be to an extreme event? In light of this problem, it is useful to be able transfer knowledge gained from one dataset or simulation to current operational data, aiding diagnosis of what the data represents. Transfer learning, a branch of machine learning, is designed for exactly these scenarios, allowing knowledge to be moved from one dataset to another. This presentation discusses exciting innovations in applying transfer learning to engineering problems, with motivating examples from non-destructive testing and aerospace applications.

About the presenter, Dr. Paul Gardner

Paul is a Research Associate at the University of Sheffield researching technologies relating to digital twins for improved dynamic design. He obtained his PhD titled 'On novel approaches to model-based structural health monitoring' from the University of Sheffield in 2019. His research interests focus on generating new simulations methods that combine machine learning and engineering modelling.

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Overcoming information sparsity in engineering datasets: a transfer learning viewpoint

P. Gardner

HBM Prenscia Technology Day - Virtual Seminar Series

November, 2020

INFORMATION SPARSITY IN DATASETS

Structural health monitoring: uses online monitoring data and a physics-based or data-based model to diagnose and predict the health state of a structure in operation

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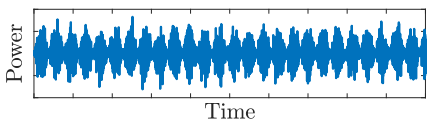

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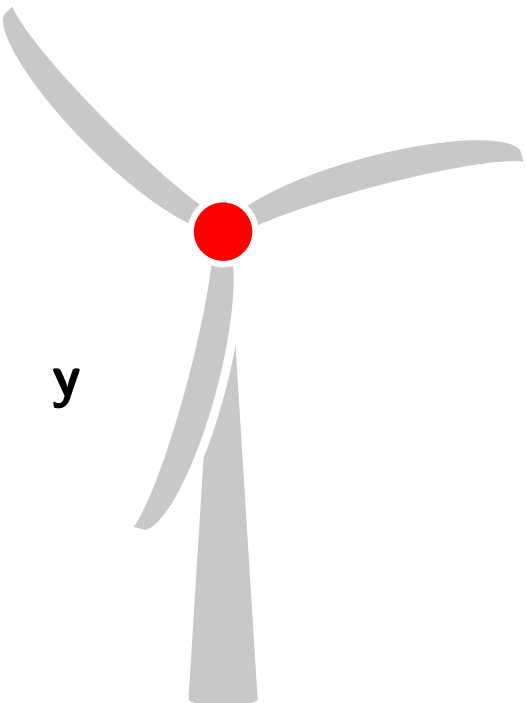

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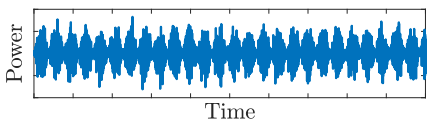

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A POPULATION-BASED VIEWPOINT

Population-based structural health monitoring: uses information from across a group of structures in order to perform and improve health state predictions for the complete population

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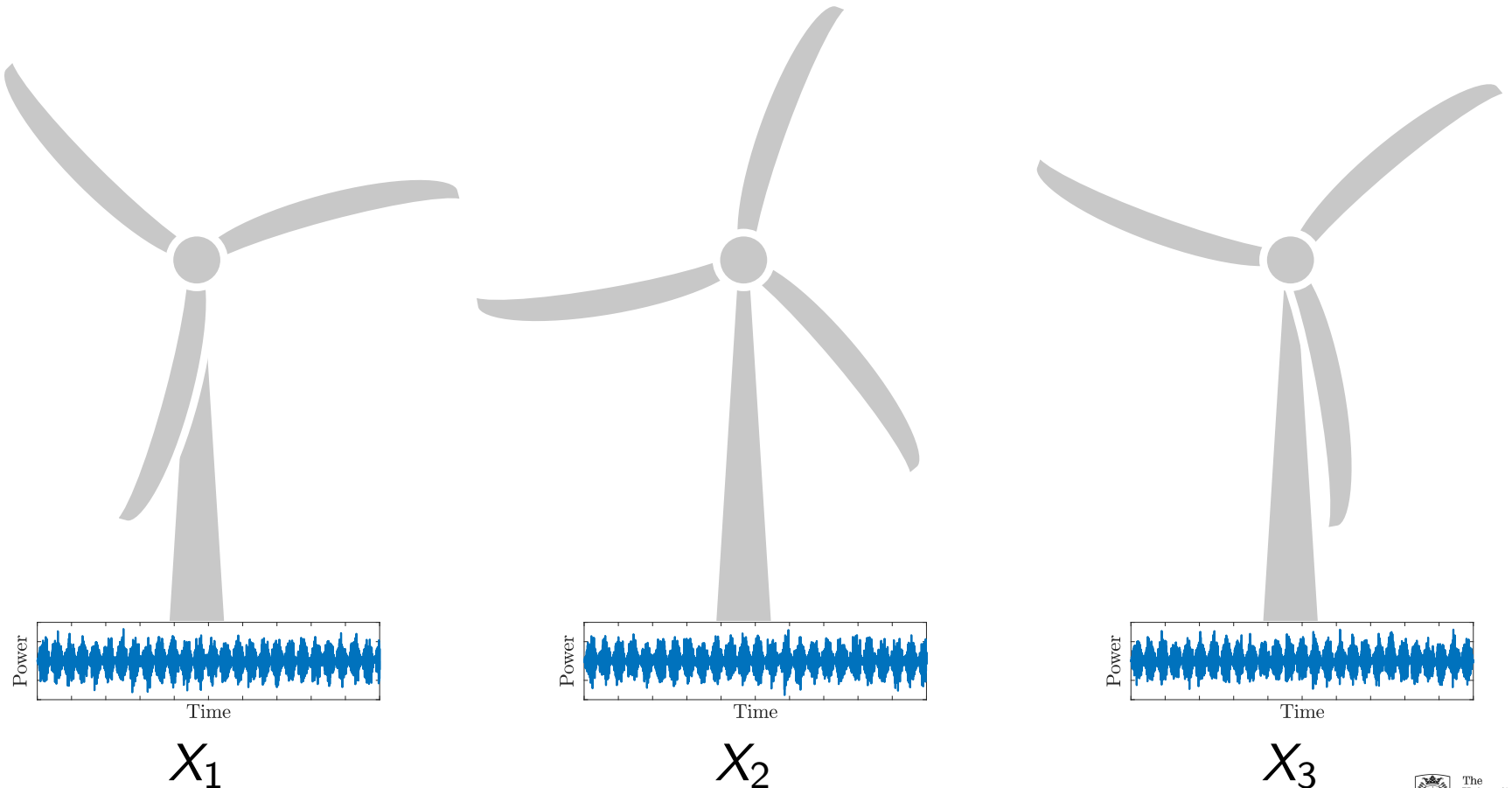

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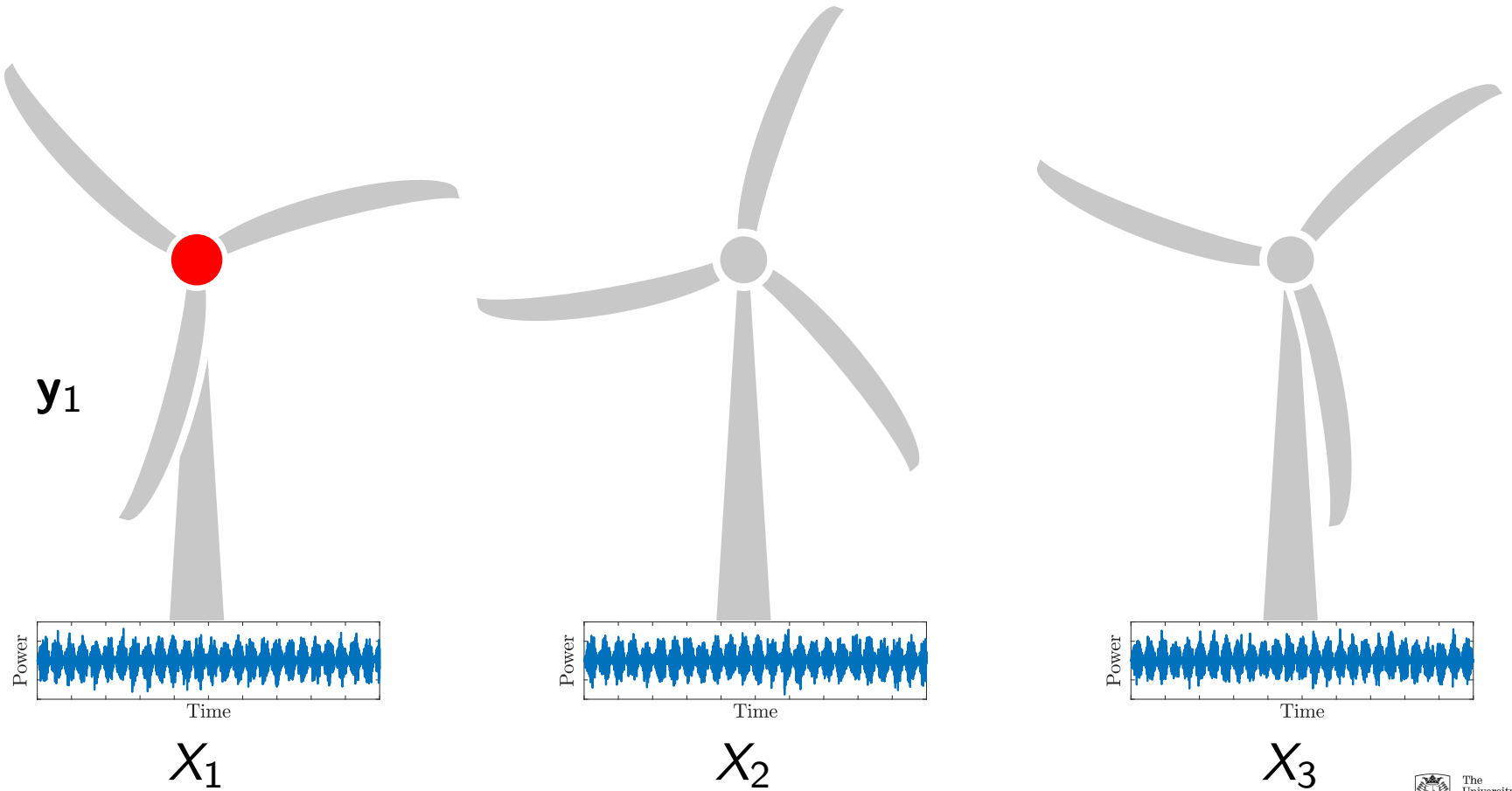

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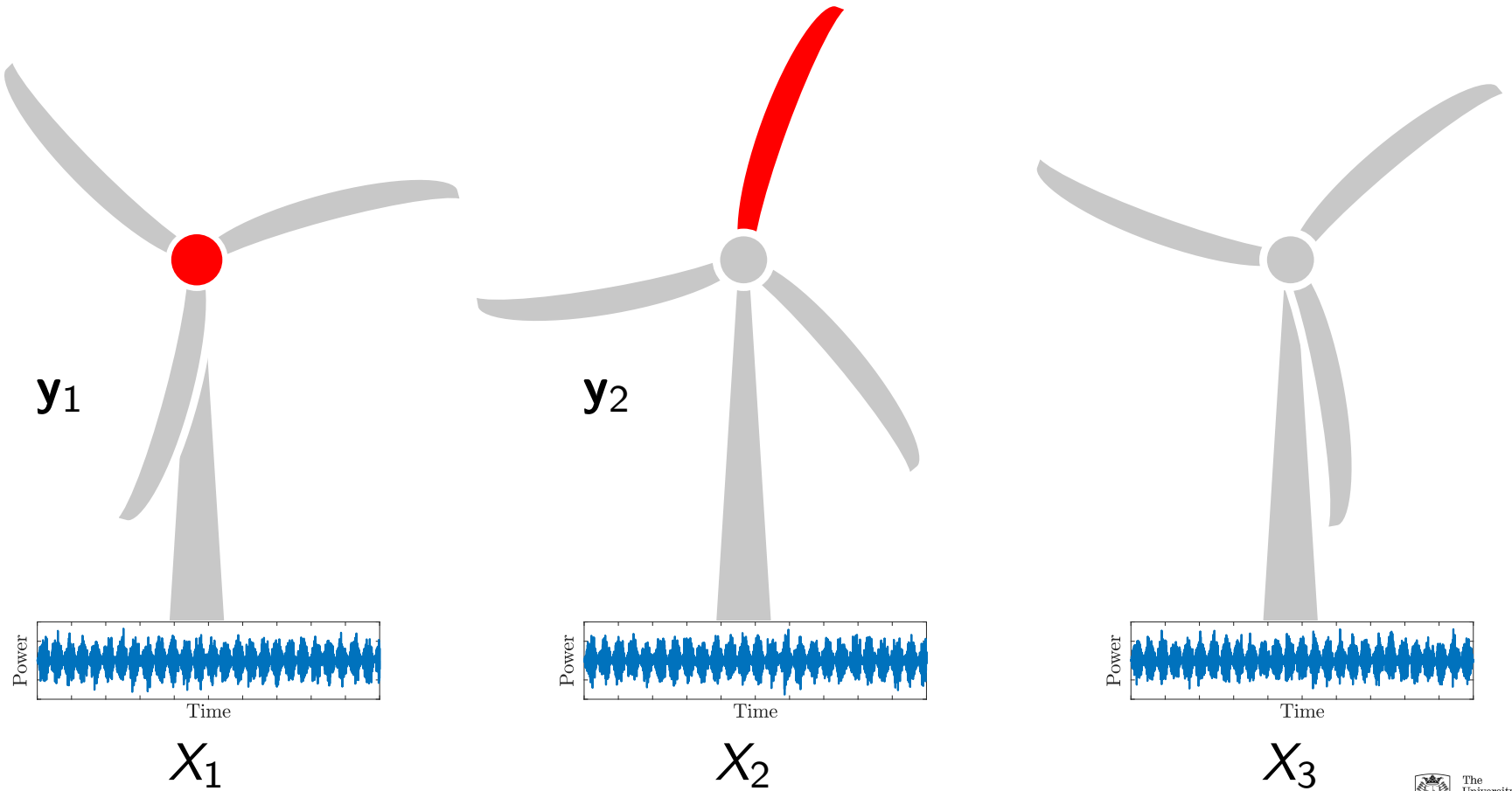

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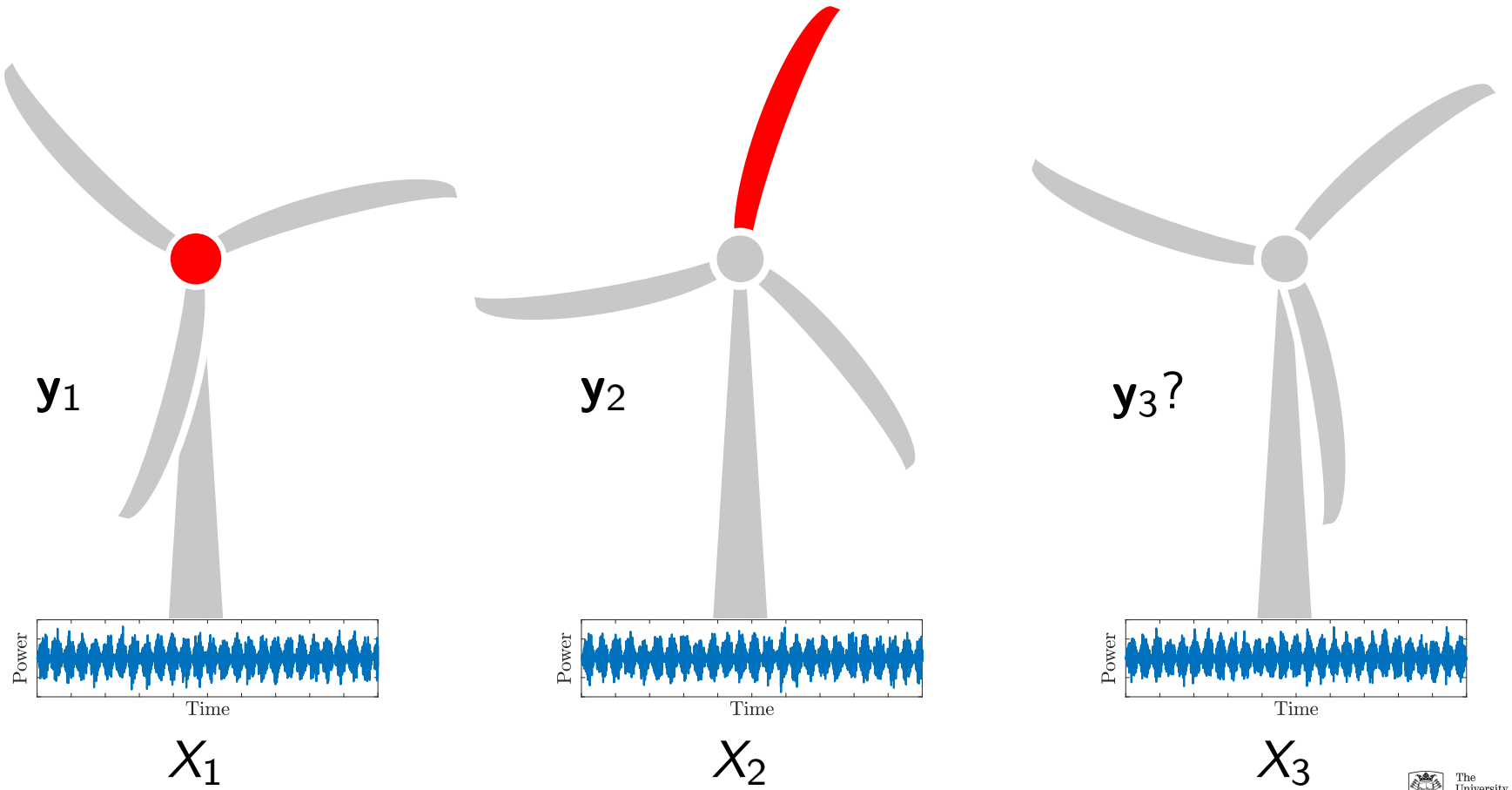

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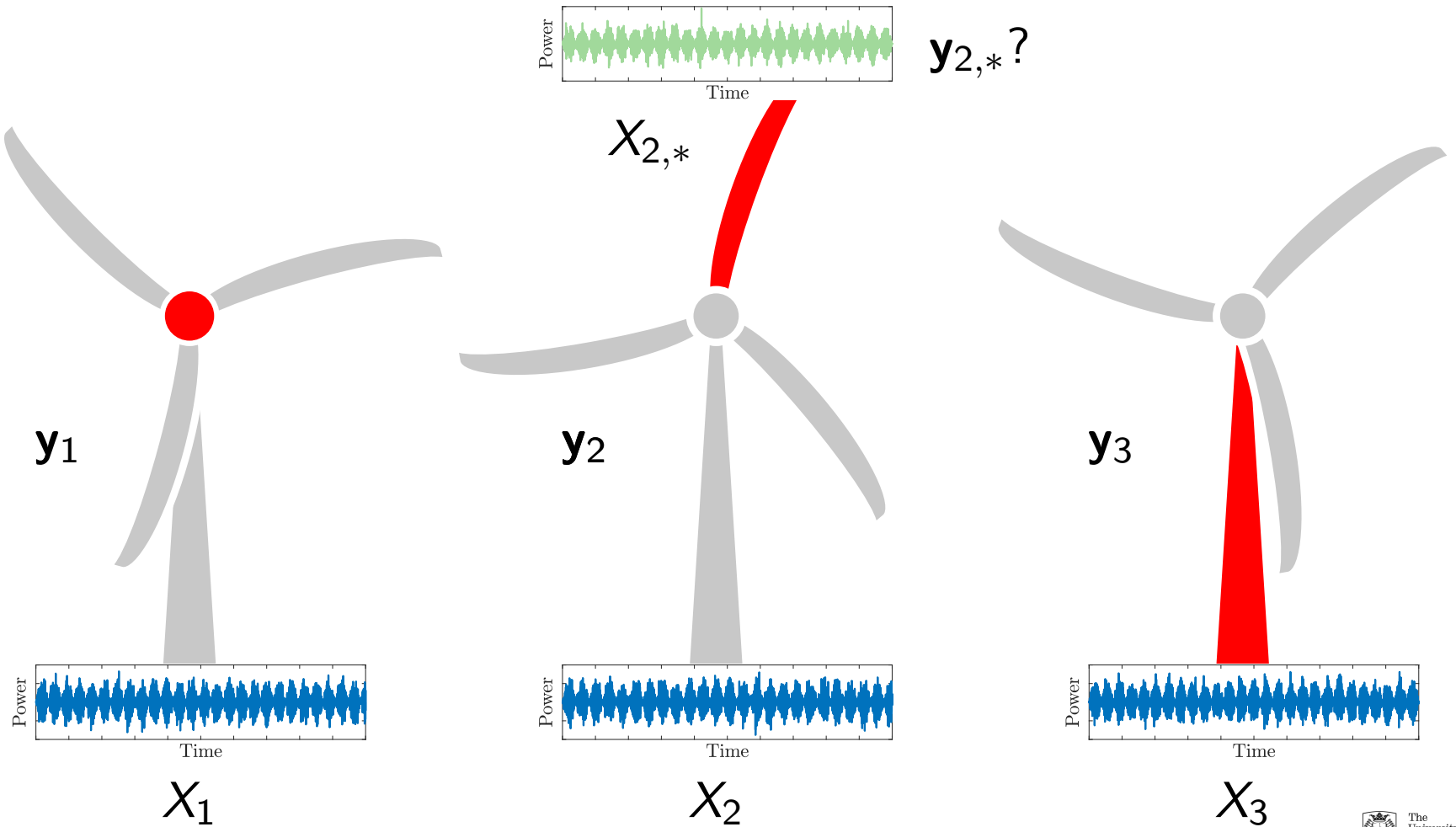

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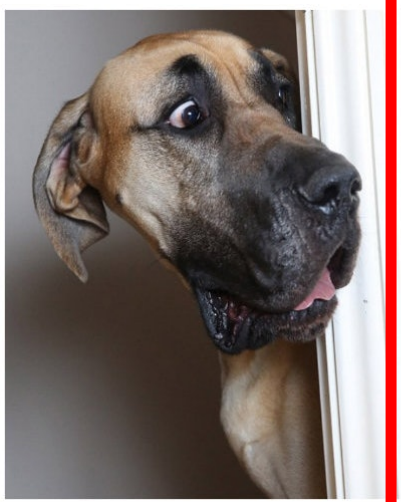
TRANSFER LEARNING

left: barkpost.com/humor/real-life-scooby-doo/
right: reddit.com/r/Eyebleach/comments/bwezzl/ladies_and_gentlemen_the_real_puss_in_boots/

TRANSFER LEARNING

Source

Real



Cartoon

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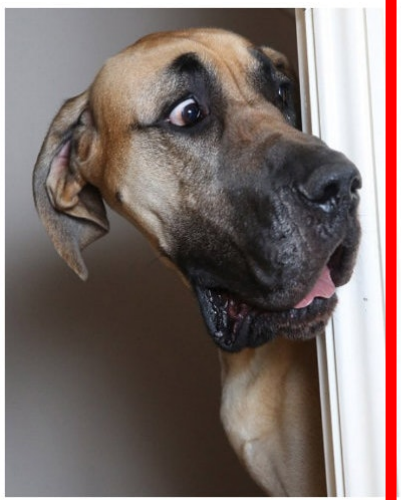
TRANSFER LEARNING

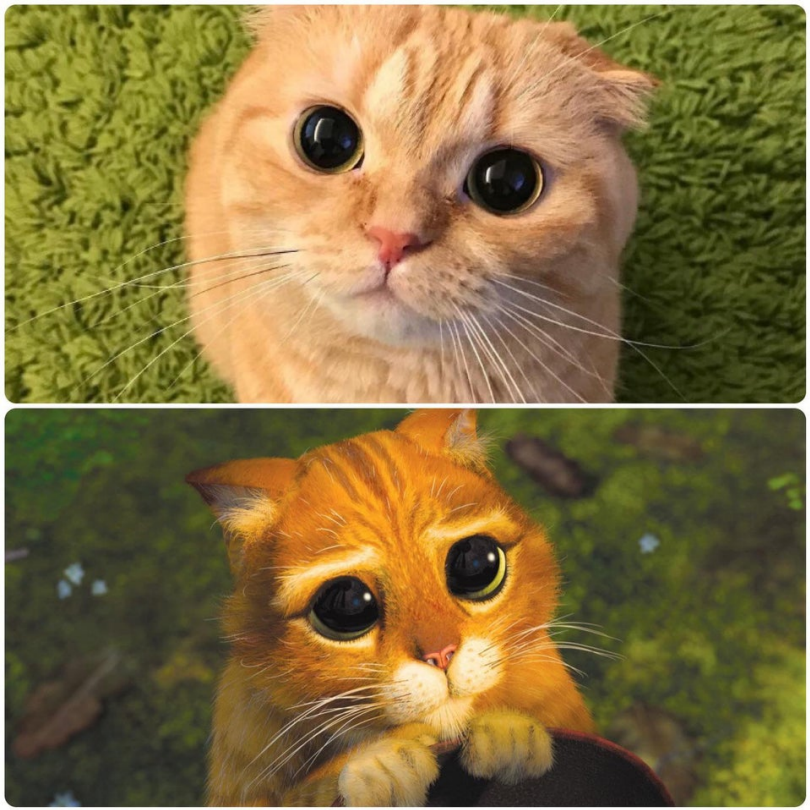
Source

Real



Cartoon

Target



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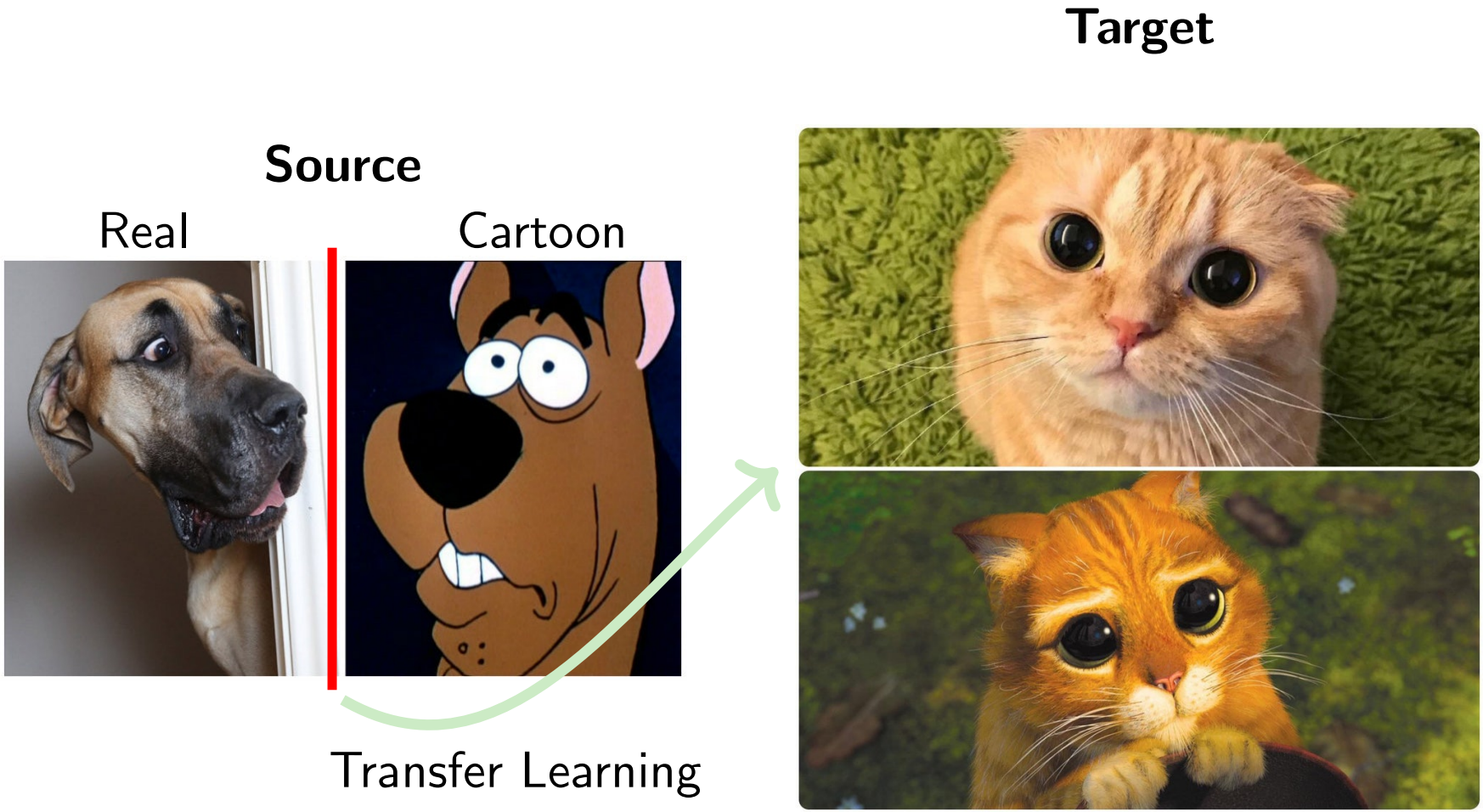

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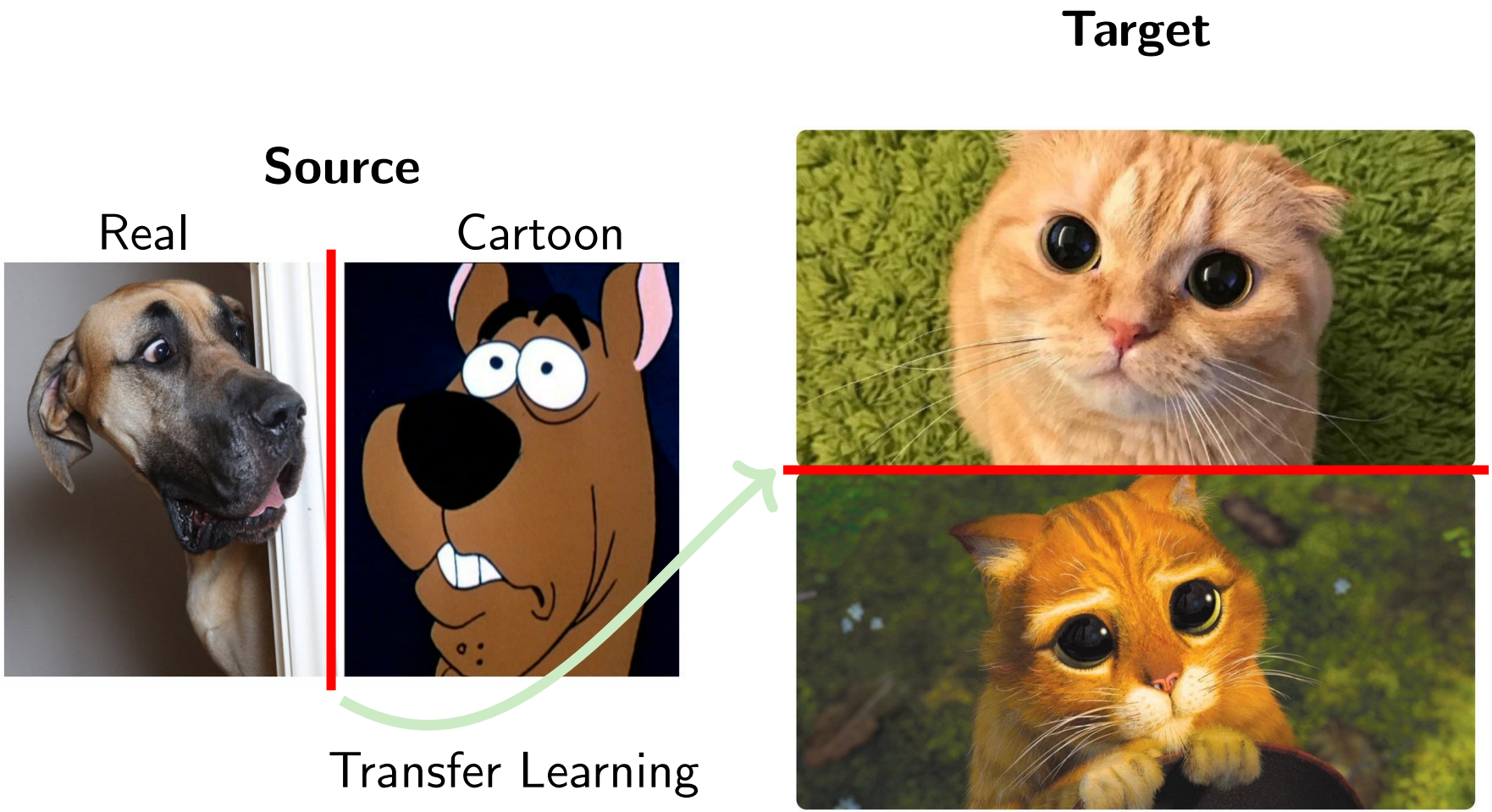

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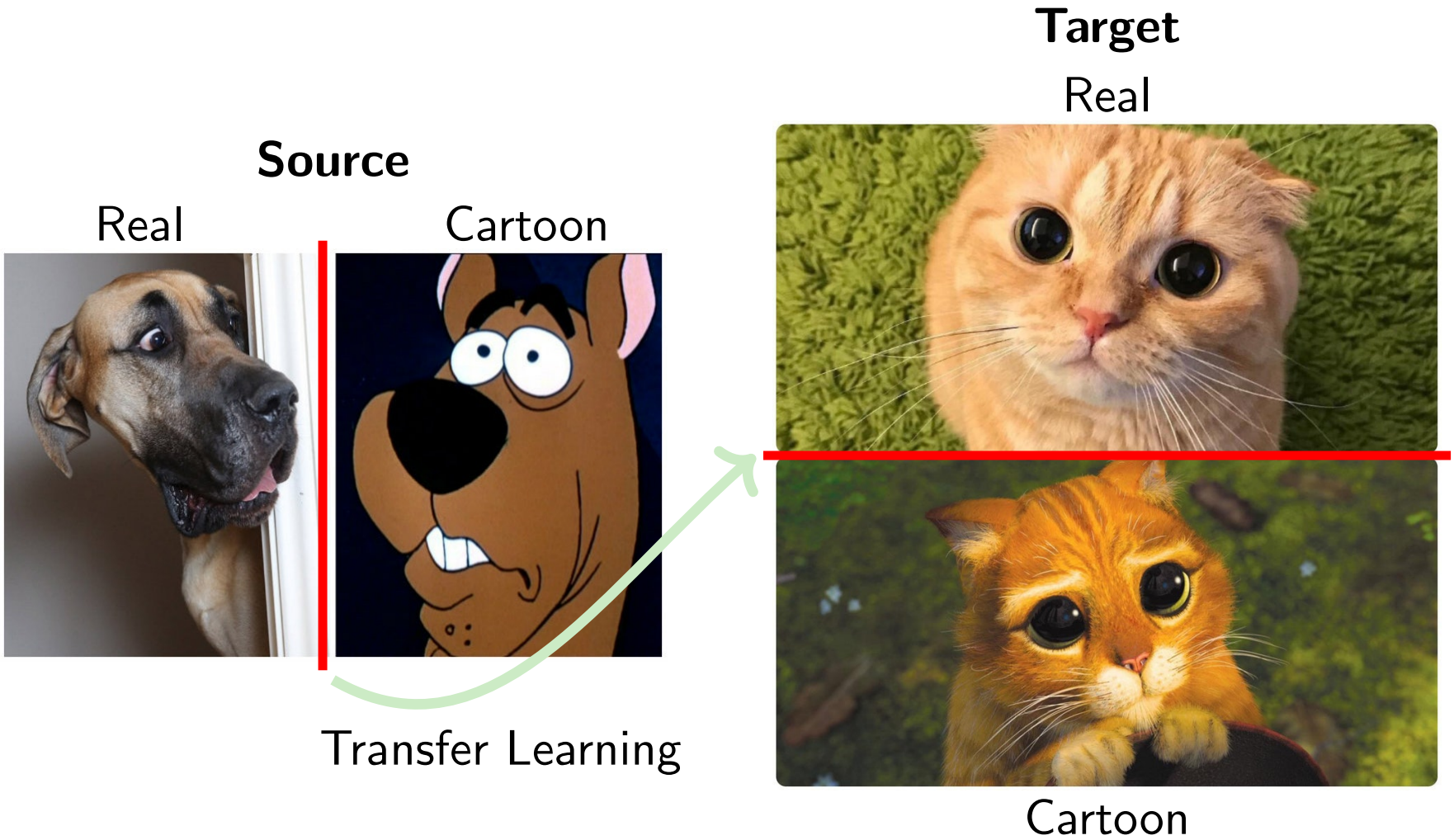

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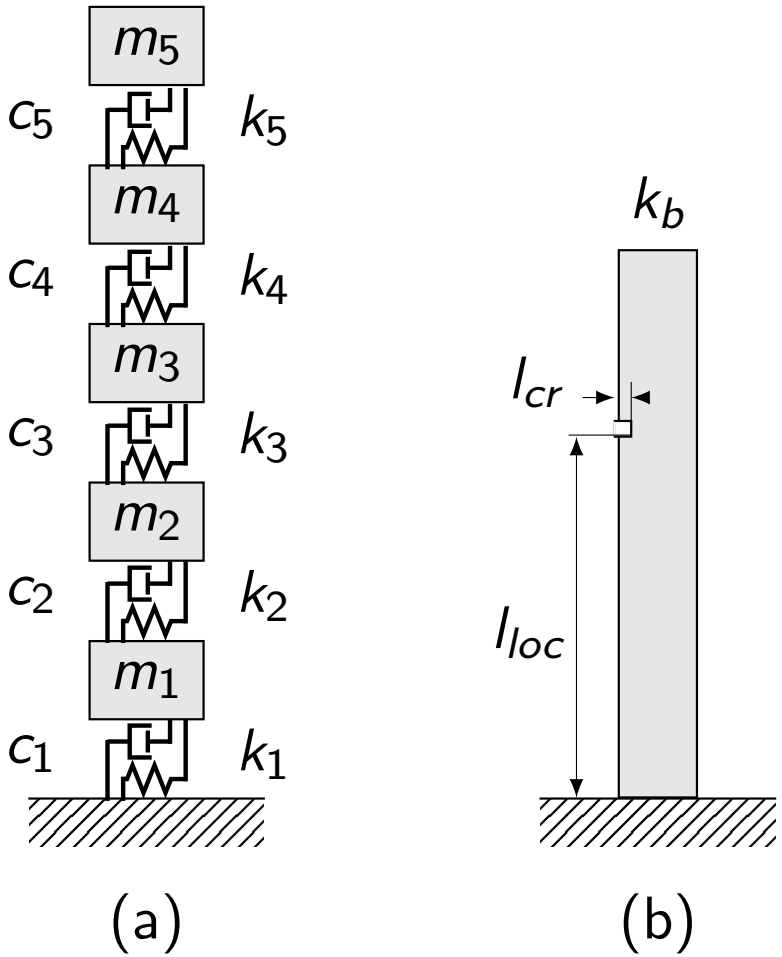
TRANSFER LEARNING EXAMPLE



$\mathcal{X} = \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5\}$
$\mathcal{Y} =$ undamaged, crack at k_1, crack at k_2, crack at k_3, crack at k_4, crack at k_5

Source and Target have nominally the same dimensions

Source and Target are steel

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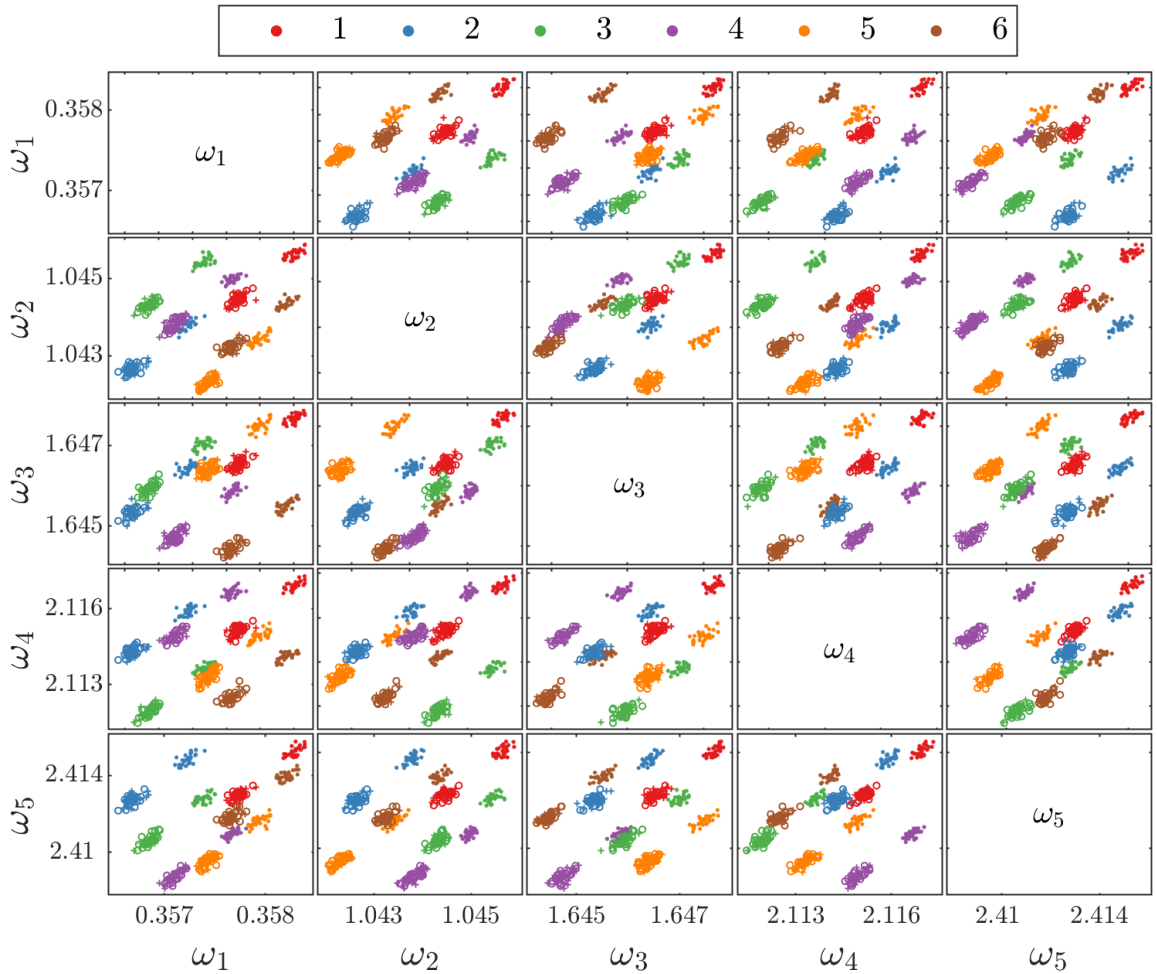
TRANSFER LEARNING EXAMPLE



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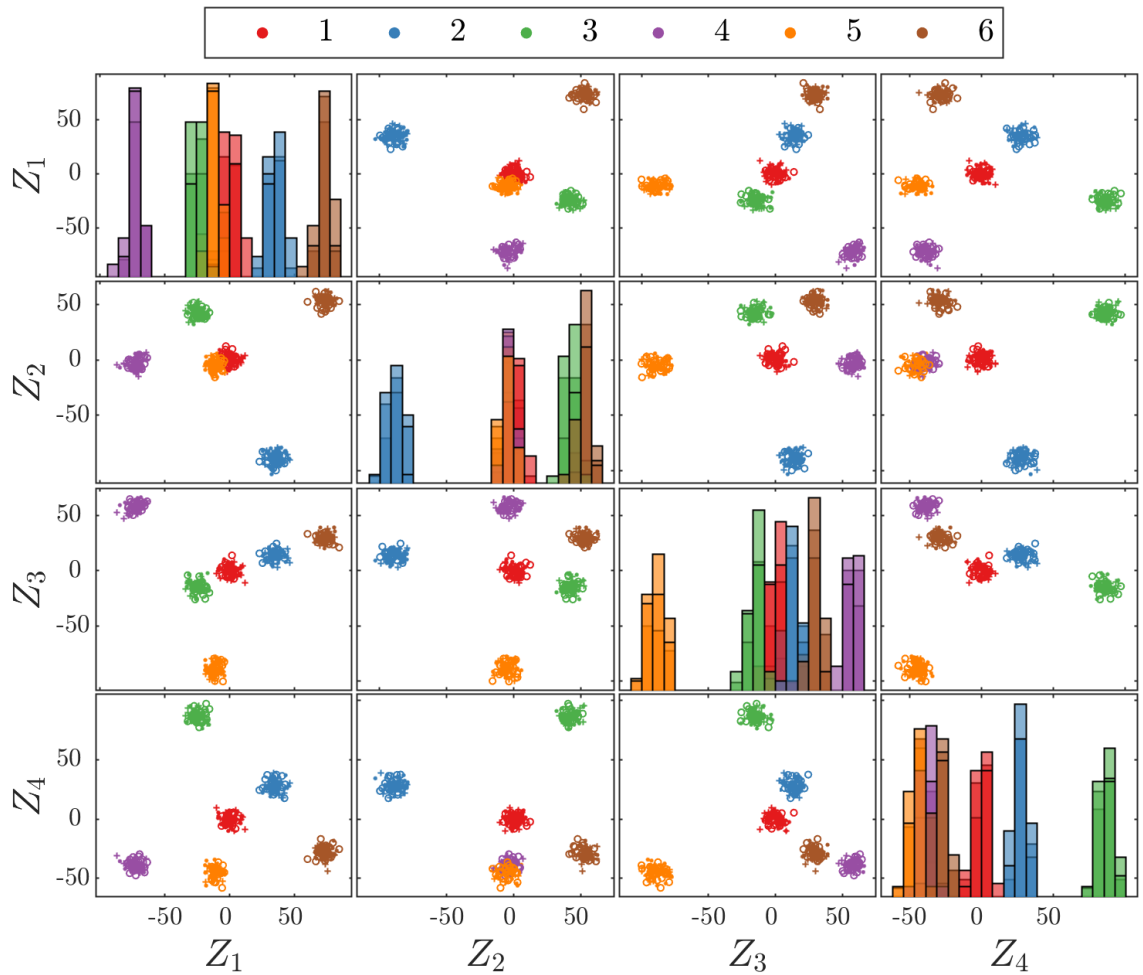
TRANSFER LEARNING EXAMPLE



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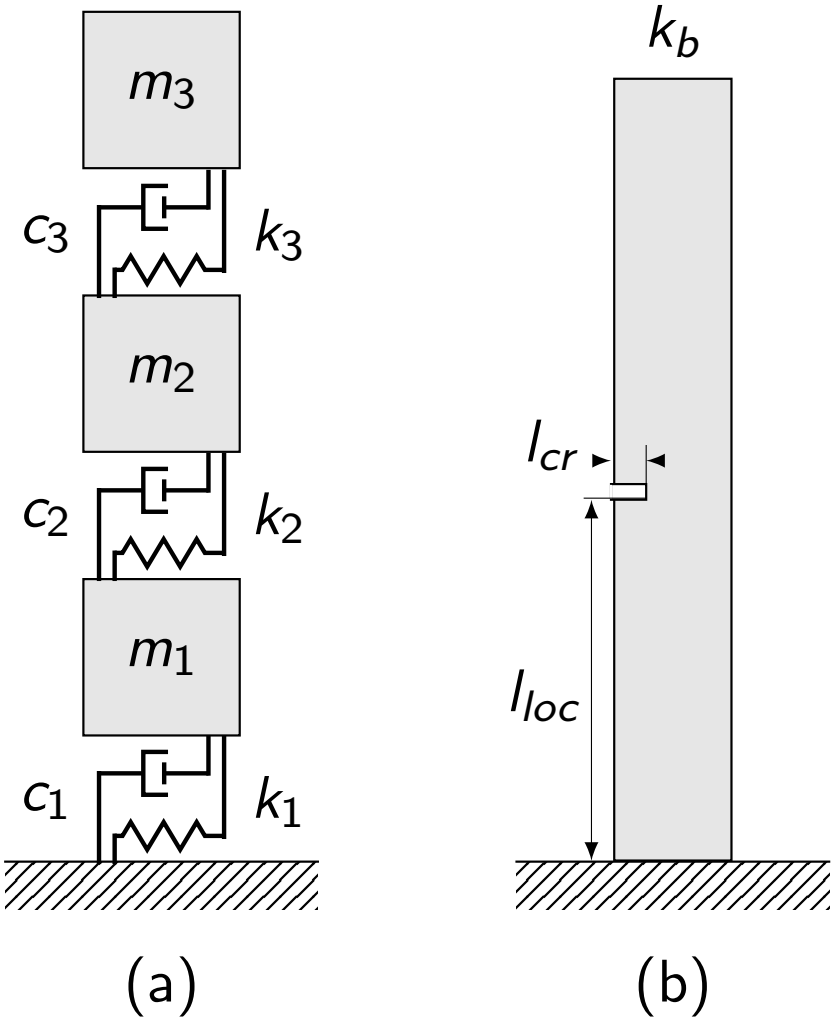
NUMERICAL-TO-EXPERIMENTAL CASE STUDY



Source **Target**

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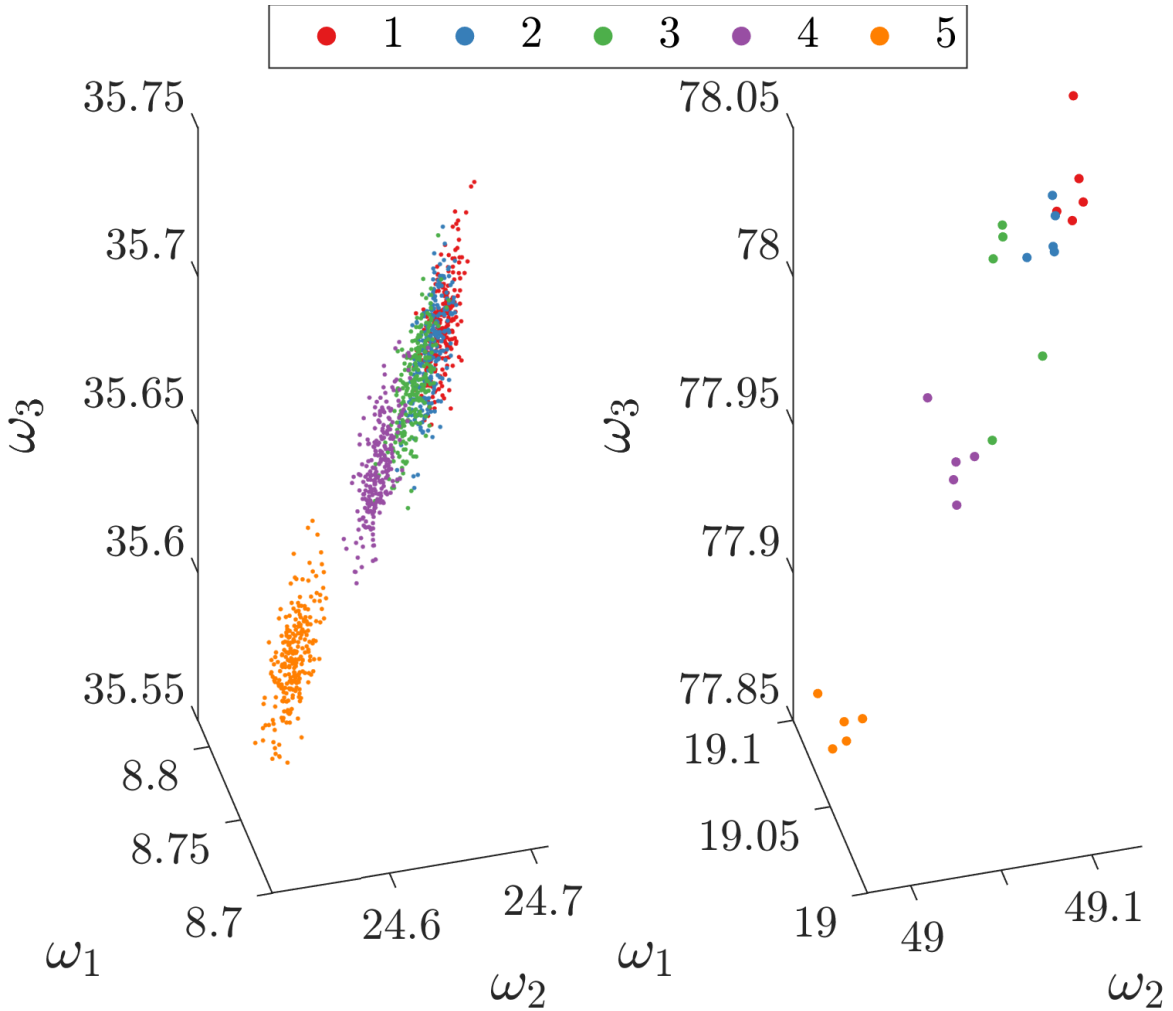

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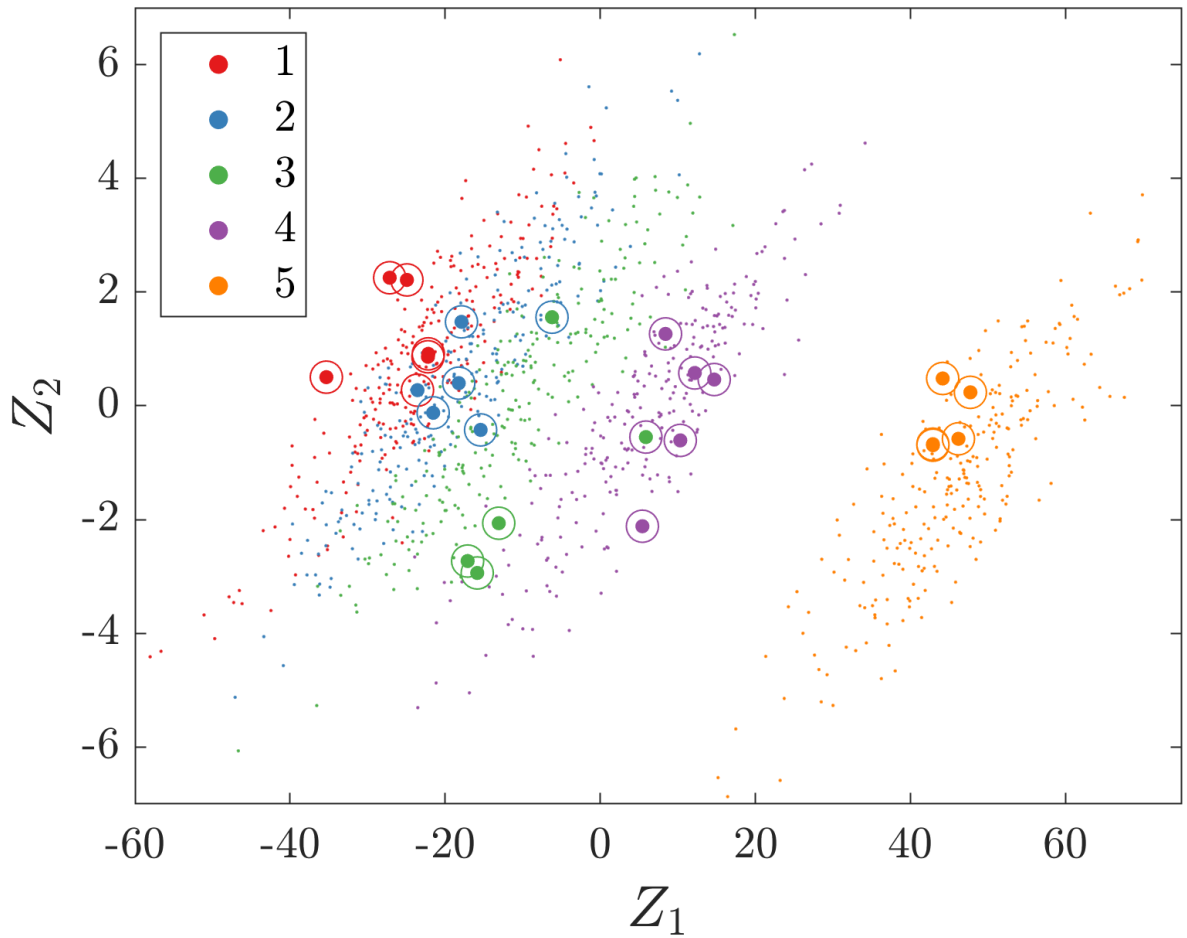

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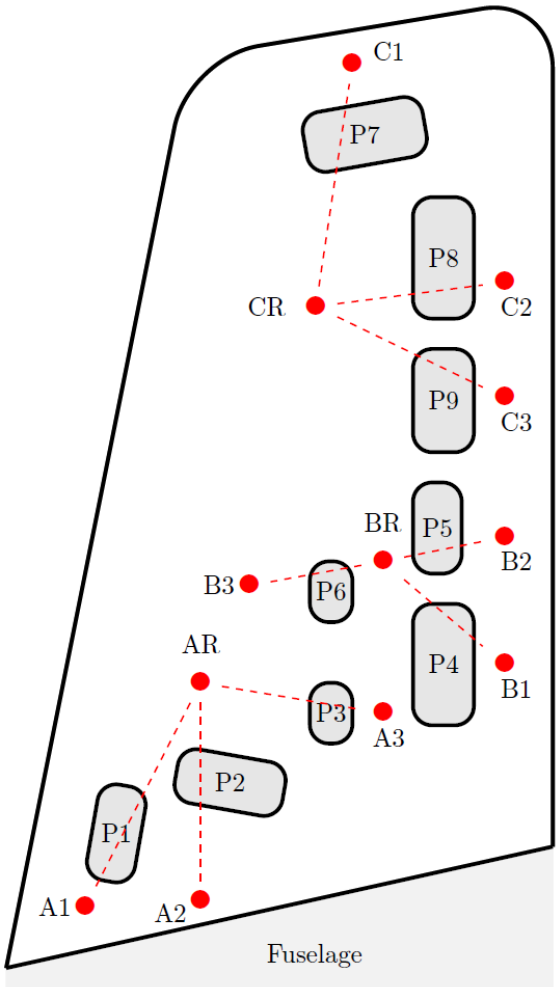
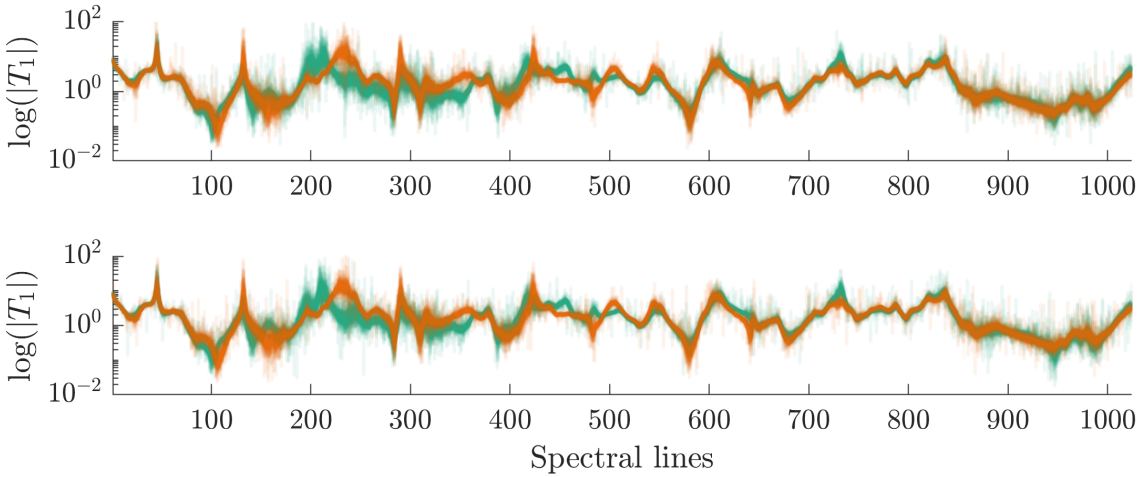
GNAT AIRCRAFT





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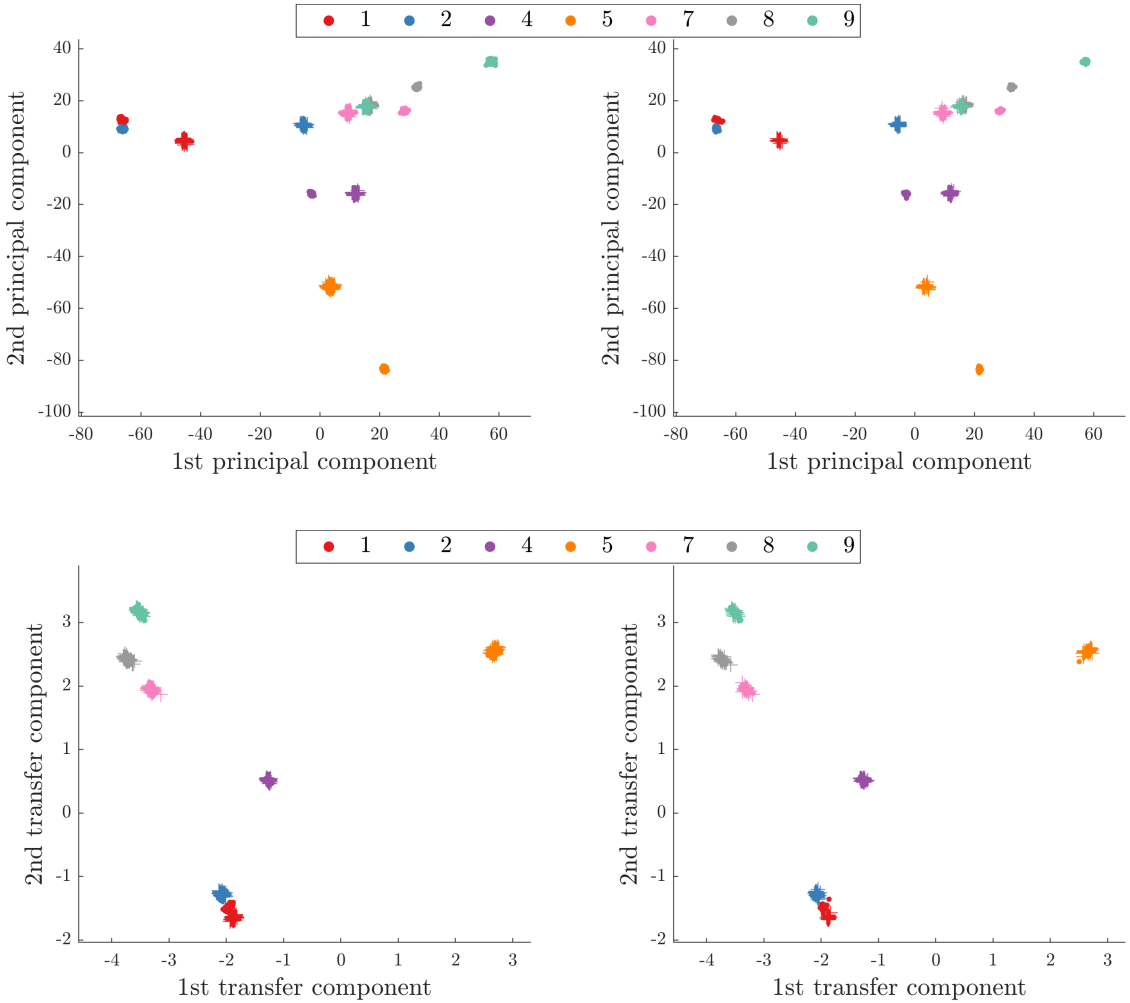

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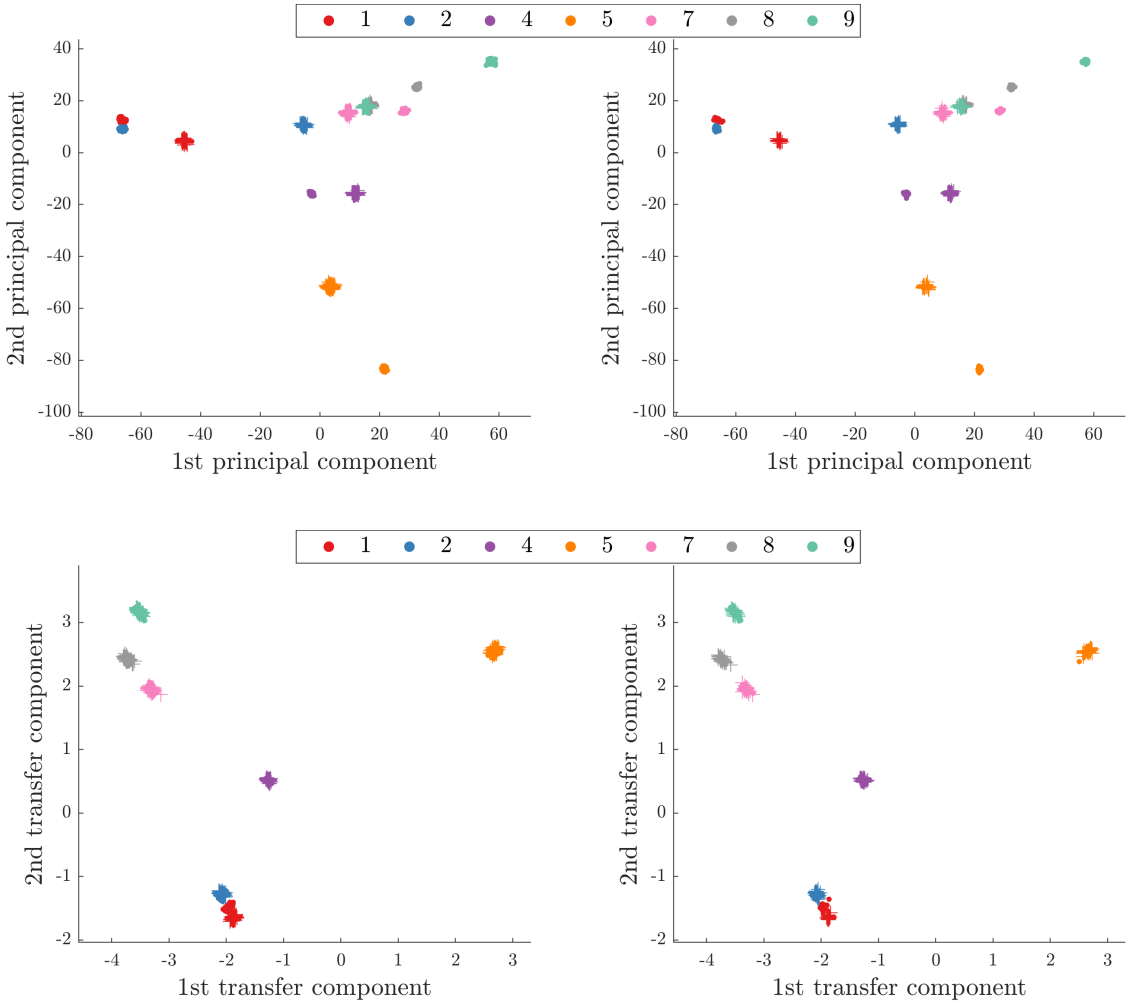

An increase from around 80% (no transfer learning) to 100% (transfer learning) classification accuracy

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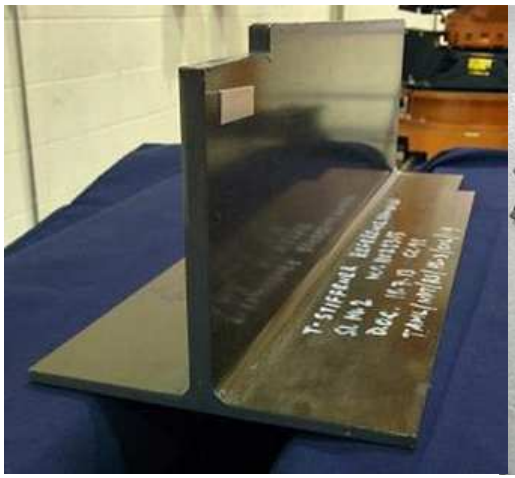
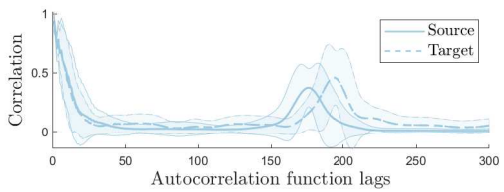
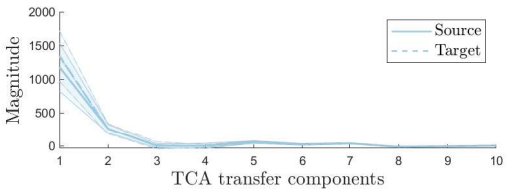
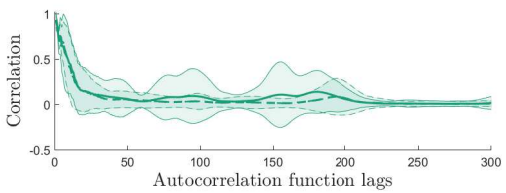
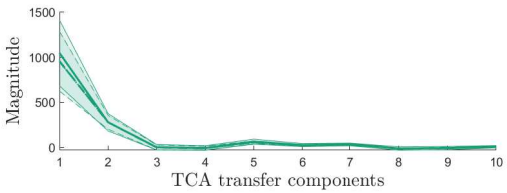
NON-DESTRUCTIVE EVALUATION











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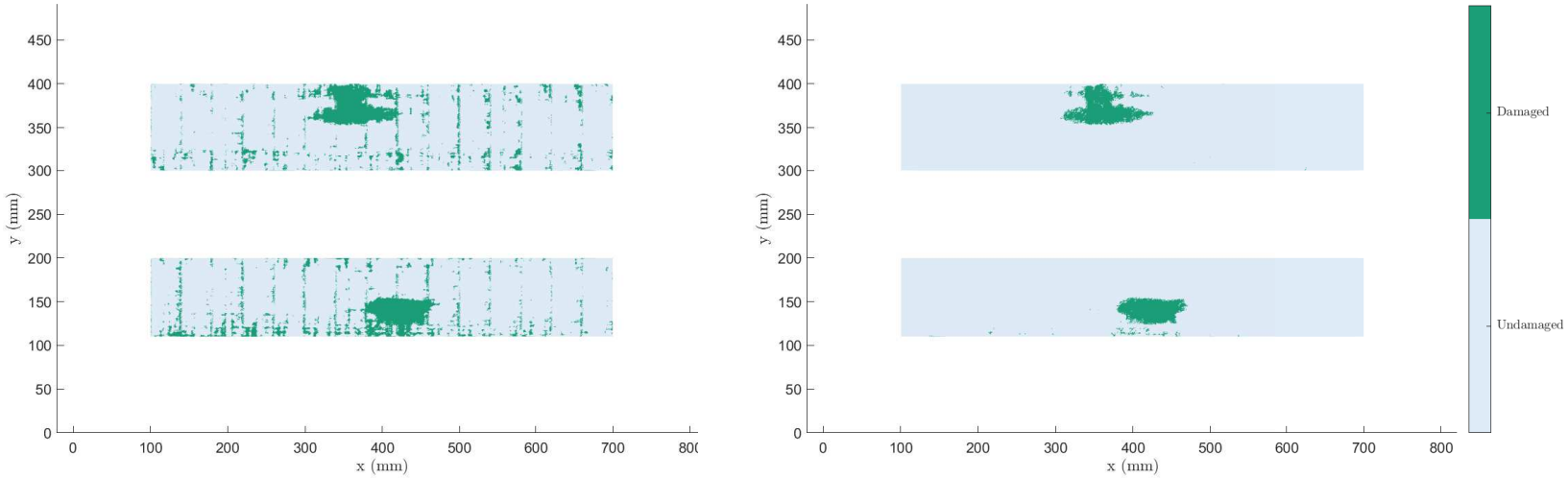

28% increase in classification performance over no transfer learning

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CONCLUSIONS AND FURTHER WORK

- Transfer learning can be used for transferring knowledge between engineering datasets overcoming issues in sparsity of information
- The approaches are widely applicable and can be applied to a variety of datasets

Acknowledgements: Engineering and Physical Sciences Research Council (EPSRC) grant refs: EP/R006768/1 and EP/R003645/1.

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Q&A

- Muhammad Afzal (Omnicell, USA)
  - Is transfer learning a sub-set of machine learning?
    - *Yes, transfer learning is a subset of machine learning. The aim of transfer learning is to utilise information from some well-defined source dataset and use this in improving a predictive function on a target dataset, therefore transferring information from the source to the target.*

- Srivatsan AV (MHI Vestas, Denmark)
  - What are the main features that are used in your ML model?
    - *The choice of what feature to use in any machine learning model is problem dependent. In a structural health monitoring context, features should be selected that have a physical correspondence with the presence of damage and if possible not be significantly affected by other benign phenomena, such as environmental conditions.*
    - *In this presentation several feature types were used. Natural frequencies are used in the first two simplistic case studies, as these capture the global behaviour of the system and will change to some degree due to the presence of damage in the form of an open crack. However, it is noted that natural frequencies are quite sensitive to other benign changes, such as temperature and environmental conditions, as well as damage, meaning that they are not very damage sensitive in general.*
    - *In the Gnat aircraft case study transmissibilities were used as features, as these capture the dynamics between two accelerometer pairs (and are output only measurements). These features are more data rich, and are able to capture changes in the local dynamics more effectively.*
    - *Finally, in the non-destructive testing case study autocorrelation functions of ultrasound pulses are used as features. These capture information about the reflection and dispersion of the wave in the material, and are significantly affected by defects in the material.*

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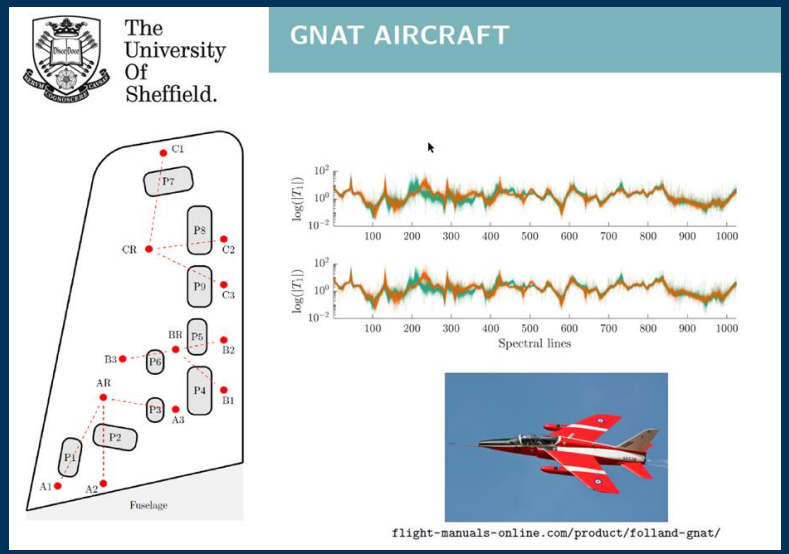

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