# An Active Transfer Learning (ATL) Framework for Smart Manufacturing with Limited Data: Case Study on Material Transfer in Composites Processing

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- Data in advanced manufacturing: challenges with limited data
- Coping with limited data: Active learning and transfer learning

## Active Transfer Learning (ATL)

- Framework architecture

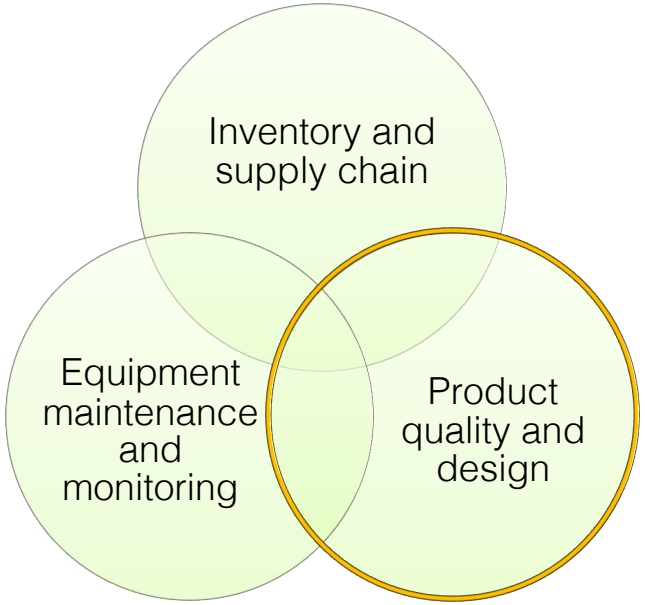
## Case study

- Material transfer in composites processing

## Summary and future work

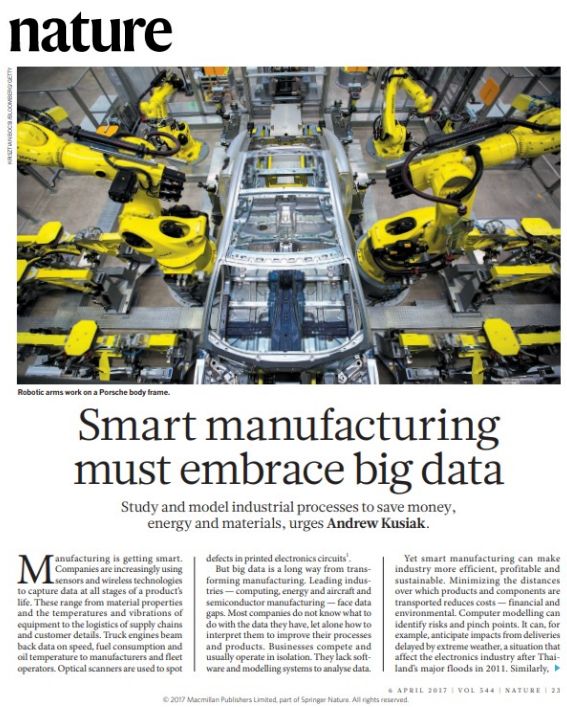
# Motivation and research objective

## Data streams in manufacturing




## 5 Vs of big data

- Volume
- Variety
- Velocity
- Veracity
- Value



nature

Robotic arms work on a Porsche body frame.

Smart manufacturing must embrace big data

Study and model industrial processes to save money, energy and materials, urges **Andrew Kusiak**.

Manufacturing is getting smart. Companies are increasingly using sensors and wireless technologies to capture data at all stages of a product's life. These range from material properties and the temperatures and vibrations of equipment to the logistics of supply chains and customer details. Truck engines beam back data on speed, fuel consumption and oil temperature to manufacturers and fleet operators. Optical scanners are used to spot defects in printed electronics circuits[1].

But big data is a long way from transforming manufacturing. Leading industries — computing, energy and aircraft and semiconductor manufacturing — face data gaps. Most companies do not know what to do with the data they have, let alone how to interpret them to improve their processes and products. Businesses compete and usually operate in isolation. They lack software and modelling systems to analyse data.

Yet smart manufacturing can make industry more efficient, profitable and sustainable. Minimizing the distances over which products and components are transported reduces costs — financial and environmental. Computer modelling can identify risks and pinch points. It can, for example, anticipate impacts from deliveries delayed by extreme weather, a situation that affect the electronics industry after Thailand's major floods in 2011. Similarly,

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Kusiak A. Nature. 2017

## Data limitations in advanced manufacturing:

- Volume → Limited and insufficient for machine learning tasks.
- Value → Available data does not fully describe the input and output space.

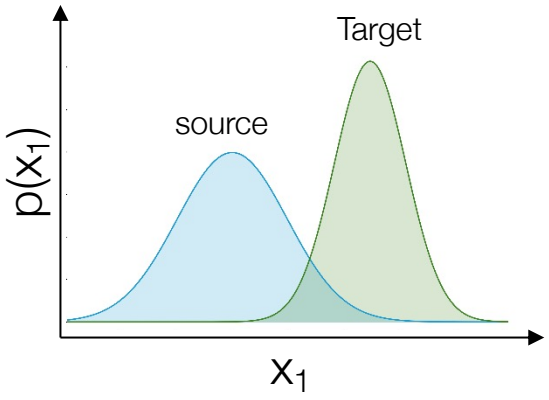
# Motivation and research objective

**Conventional ML** models assumption about data:

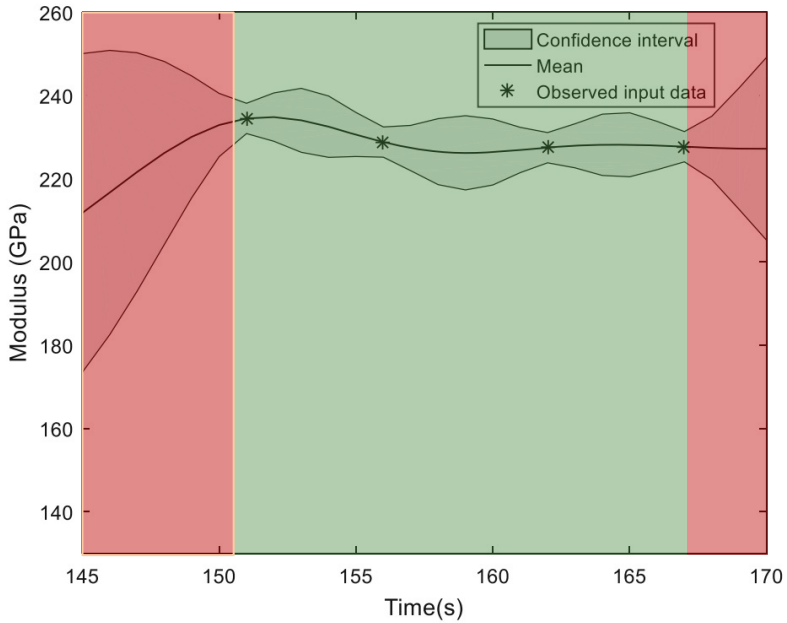
- Training set size is sufficient for developing the model.
- The training and test data are drawn from the same probability distribution:

$$p_{training}(x) = p_{test}(x)$$

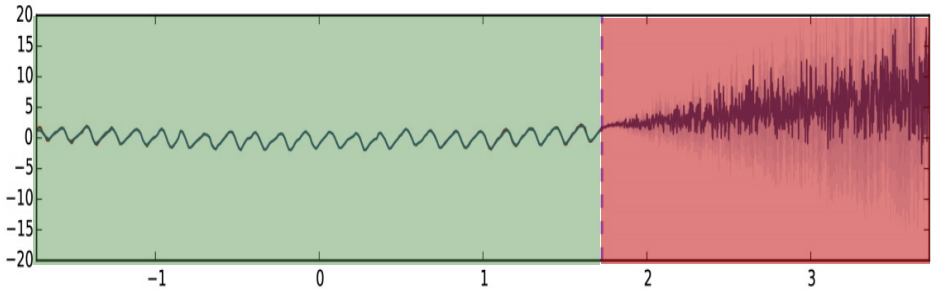
Covariate shift




$$p(x^s) \neq p(x^t)$$




Ramezankhani, M, et al. "A multi-objective Gaussian process approach for optimization and prediction of carbonization process in carbon fiber production under uncertainty." Advanced Composites and Hybrid Materials 2.3 (2019): 444-455.




Gal, Y, and Ghahramani, Z. "Dropout as a bayesian approximation: Representing model uncertainty in deep learning." international conference on machine learning. PMLR, 2016.`

# Motivation and research objective

Conventional ML models assumption about data

- Training and test data are drawn from the same probability distribution:

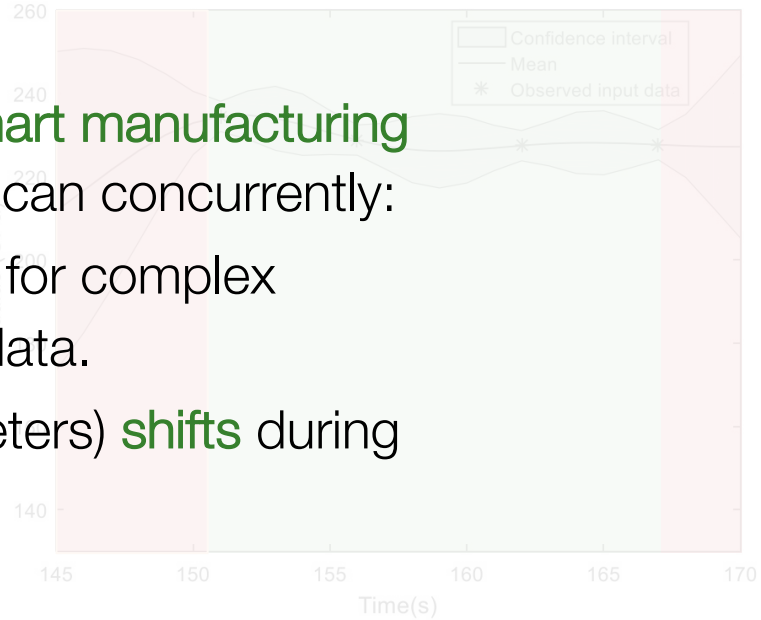
$$p_{training}(x) = p_{test}(x)$$

Overcome the shortfalls of conventional ML for current smart manufacturing implementations by developing a learning framework that can concurrently:

1. Establish reliable prediction and optimization models for complex manufacturing processes in the presence of limited data.
2. Be immune (robust) against domain (process parameters) shifts during the production/design *of new parts.*

Covariate shift


$$p(x^s) \neq p(x^t)$$

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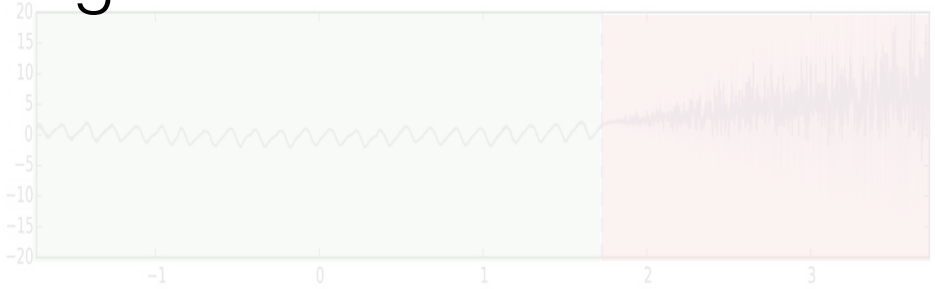
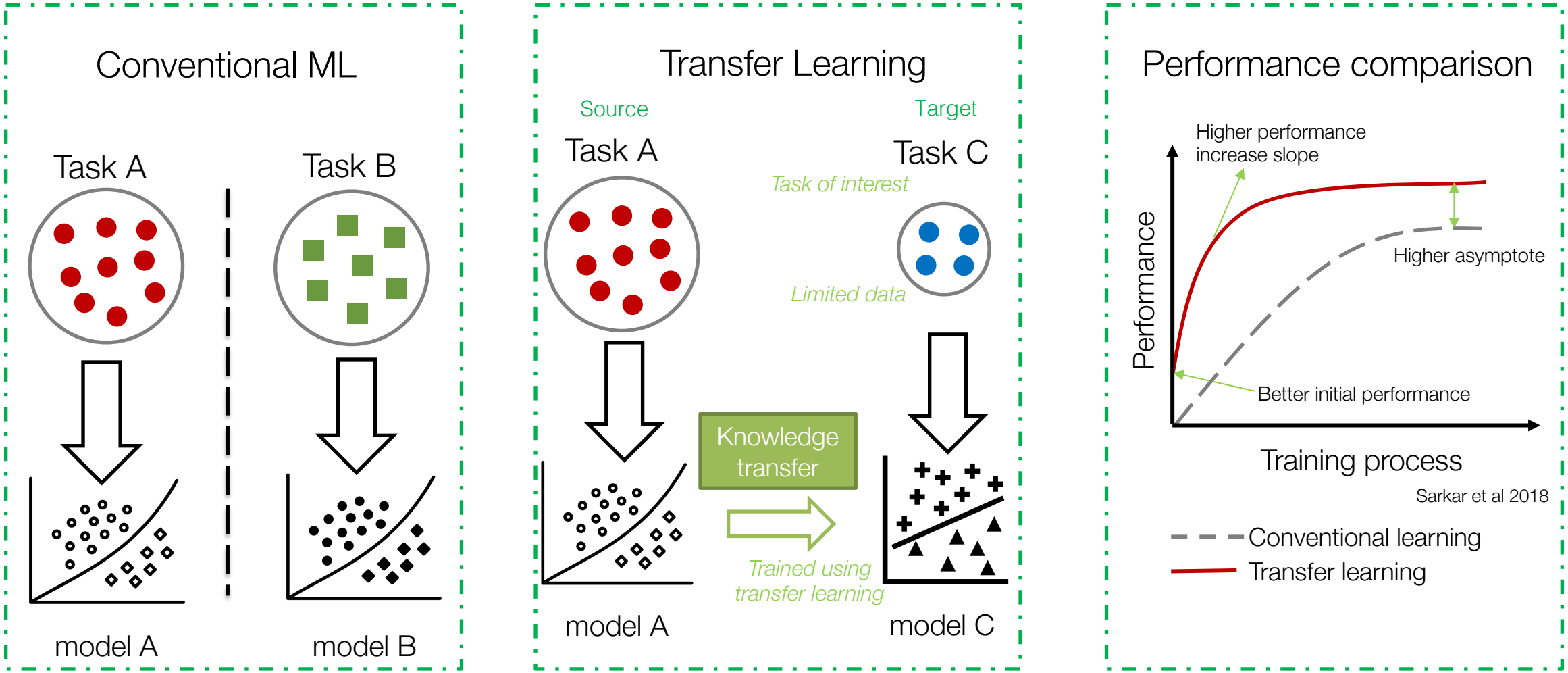
## Active Transfer Learning



Gal, Y, and Ghahramani, Z. "Dropout as a bayesian approximation: Representing model uncertainty in deep learning." international conference on machine learning. PMLR, 2016.

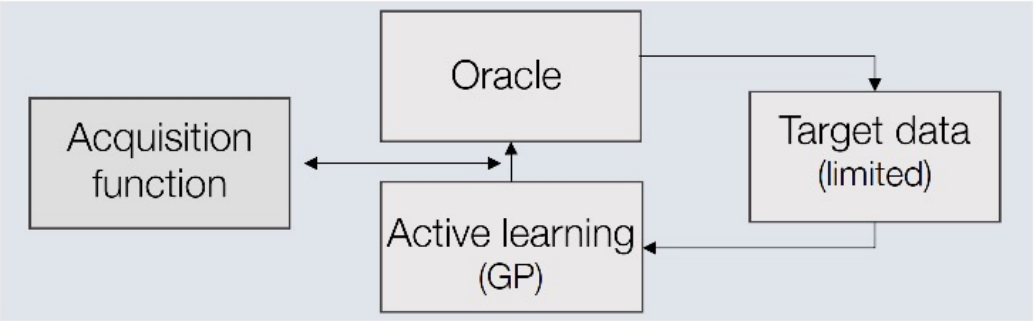
# Transfer Learning

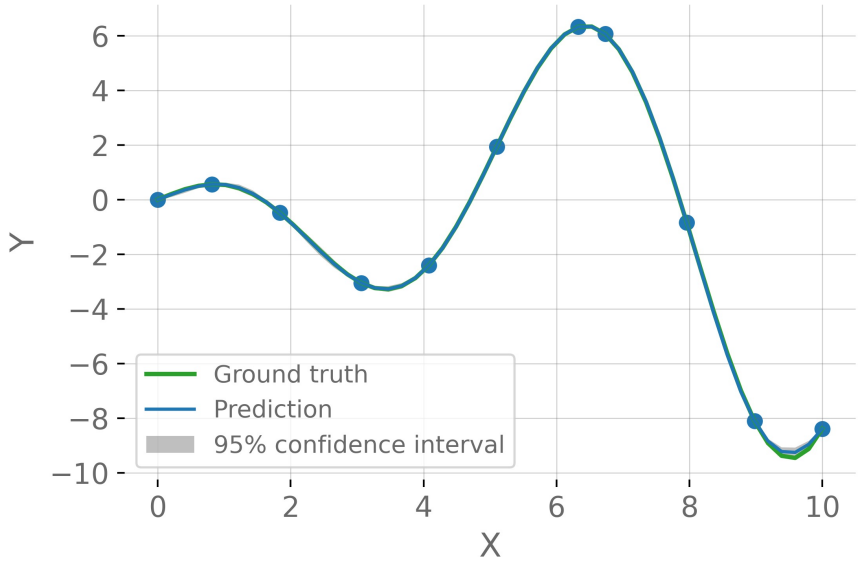


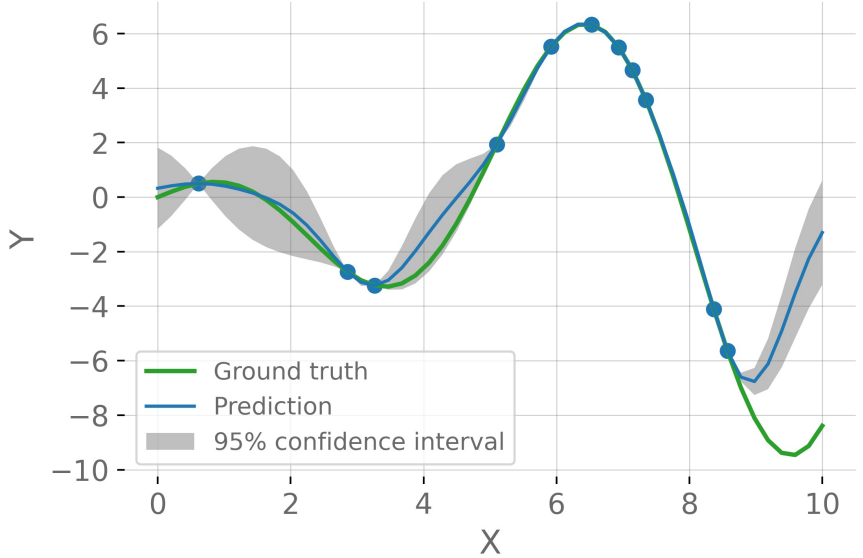
# Active Learning

- Closely related to Optimal Experimental Design
- Estimating the density function $P(y|x)$ with limited trials:
    - **Uncertainty reduction**: The unknown function of interest (i.e., mapping between inputs and outputs) is learned by minimizing the uncertainty about the posterior distribution.

Active Learning Architecture



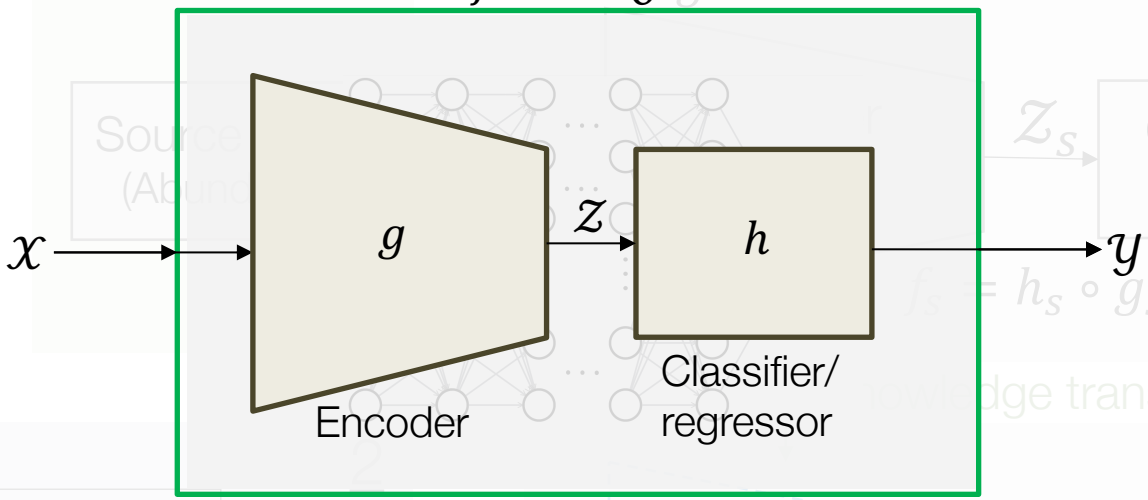
# Active Transfer Learning - Architecture

ATL Procedure:

1. Training the source model from scratch
2. Acquiring limited data via active learning
3. Training the target model using transfer learning

$$f = h \circ g$$

$$f: \mathcal{X} \rightarrow \mathcal{Y}$$



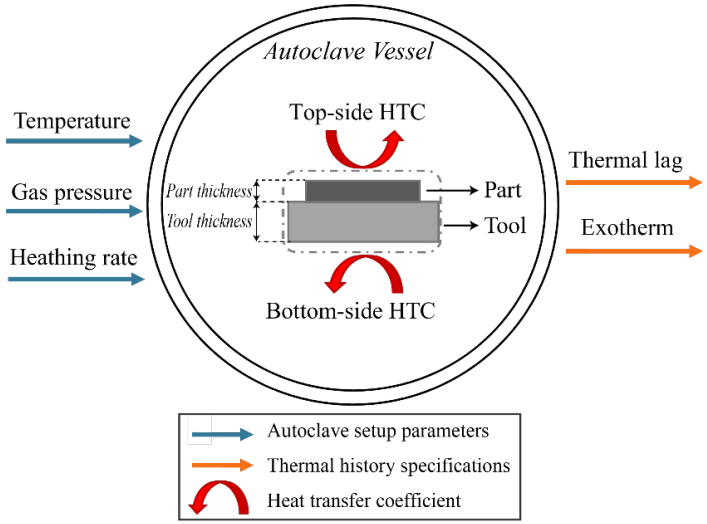

$$g: \mathcal{X} \rightarrow \mathcal{Z} \qquad h: \mathcal{Z} \rightarrow \mathcal{Y}$$

# Case study: Material transfer in composites manufacturing – Problem statement

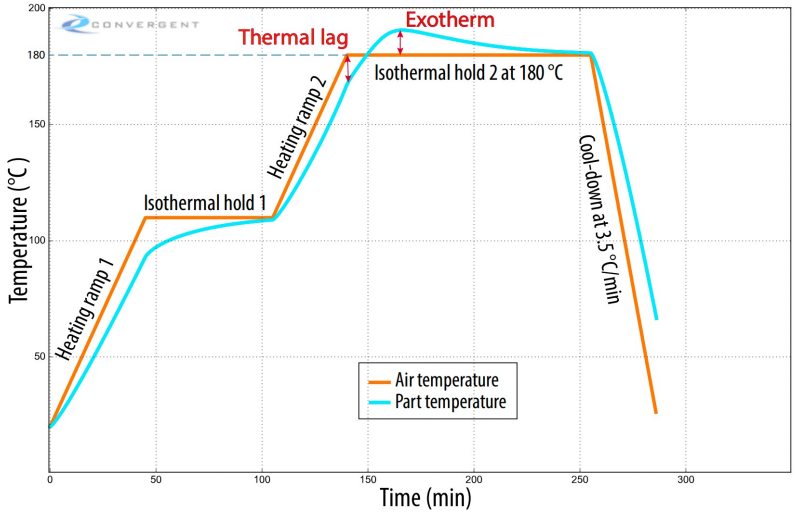
Interior of an industrial autoclave in composite manufacturing

Ramezankhani, M., et al. "**Making Costly Manufacturing Smart with Transfer Learning Under Limited Data: A Case Study on Composites Autoclave Processing**." Journal of Manufacturing Systems.

Schematic of autoclave curing process in aerospace composites manufacturing




Two-hold autoclave cure cycle




Source material:
**AS4/8552**
(Abundant historical data)

→

Target material:
**AS4/8551**
(No data; to be sampled/limited)

Classification problem: Pass/Fail per part's **thermal history**

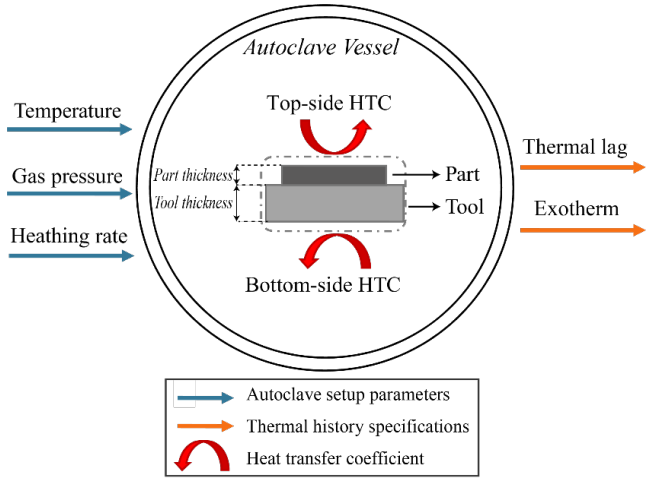
CRN Composites Research Network

# Case study: Material transfer in composites manufacturing – Methodology

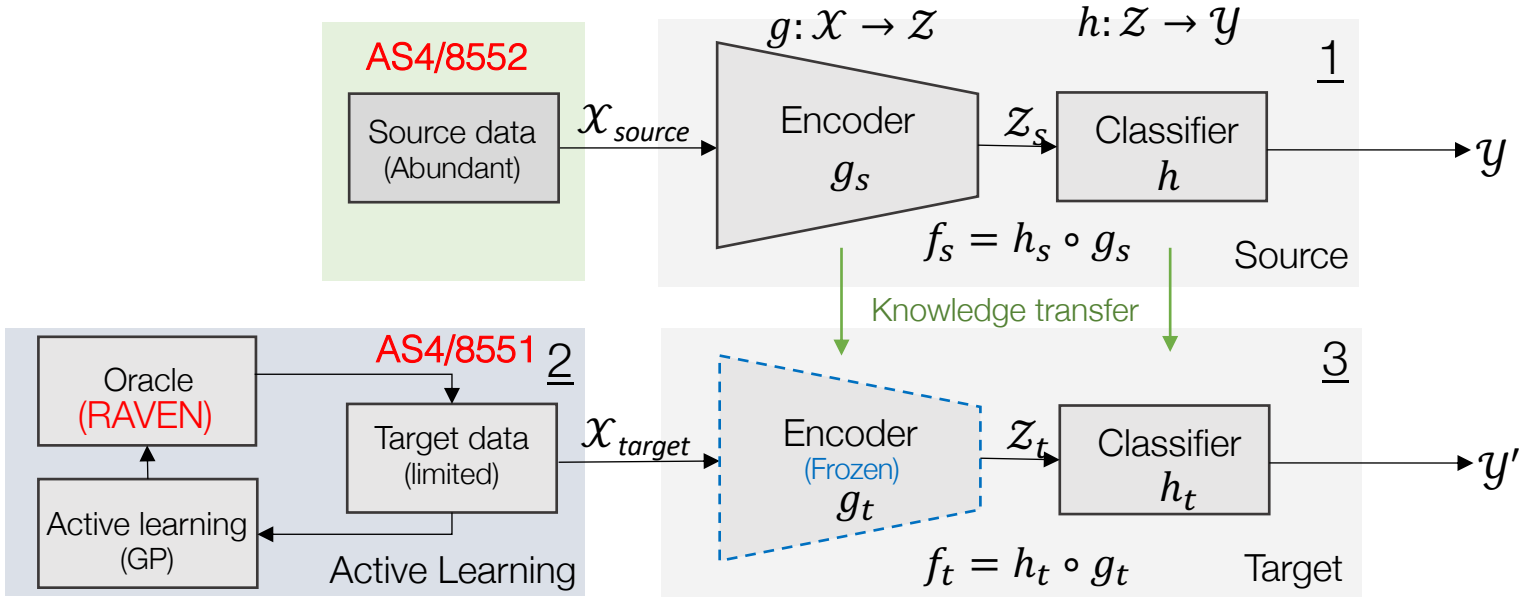
**RAVEN** performs thermal, physical and mechanical property estimation for given part configurations and cure cycles, and outputs the thermal history of the composite material.

Source material: **AS4/8552** (Abundant historical data) → Target material: **AS4/8551** (No data; to be sampled/limited)

Classification problem: Pass/Fail per part's **thermal history**




| Input variables | Values | |
|---|---|---|
| Tool material | 6061 Aluminum; AS4/8552 Composite; Invar 36; SAE 1020 Steel | |
| | **Min** | **Max** |
| Tool thickness (mm) | 2.5 | 20 |
| Part thickness (mm) | 2.5 | 20 |
| Heat rate – ramp 1 (°C/min) | 1 | 5 |
| Isothermal hold 1 (°C) | 105 | 125 |
| Heat rate – ramp 2 (°C/min) | 1 | 5 |
| Top-side HTC (W/m²K) | 10 | 125 |
| Bottom-side HTC (W/m²K) | 10 | 125 |



# Case study: Material transfer in composites manufacturing – Results

Gaussian Processes (GP) classification:

$p(y^*|x^*, X, f) \sim \mathcal{N}(\bar{y}^*, v^*)$

$\bar{y}^* = K(x^*, X)[K(X, X) + \sigma_n^2 I]^{-1} y$

$v^* = K(x^*, x^*) - K(x^*, X)[K(X, X) + \sigma_n^2 I]^{-1} K(X, x^*)$

In GP:
Maximize **differential entropy score**:

$\Delta_j \triangleq H[p(y_j)] - H[p^{new}(y_j)]$

Equivalent to finding the point with the **highest variance**

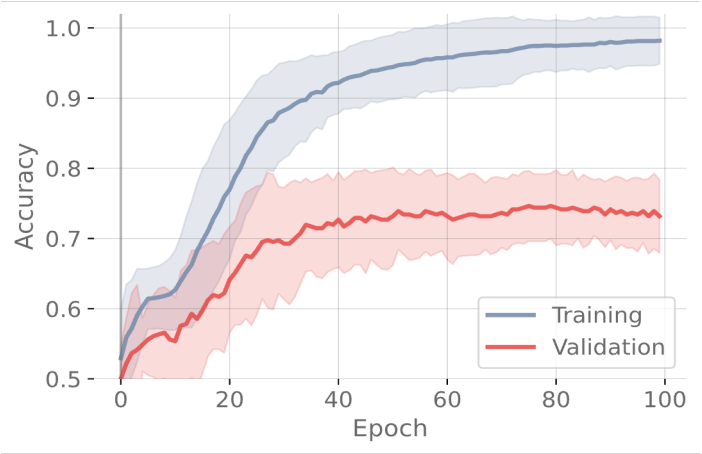
Differential entropy (STD): $x^* = \text{argmax}_{x \in \mathcal{D}_{\text{Pool}}} v$

Decision boundary: $x^* = \text{argmin}_{x \in \mathcal{D}_{\text{Pool}}} |\bar{y}|$

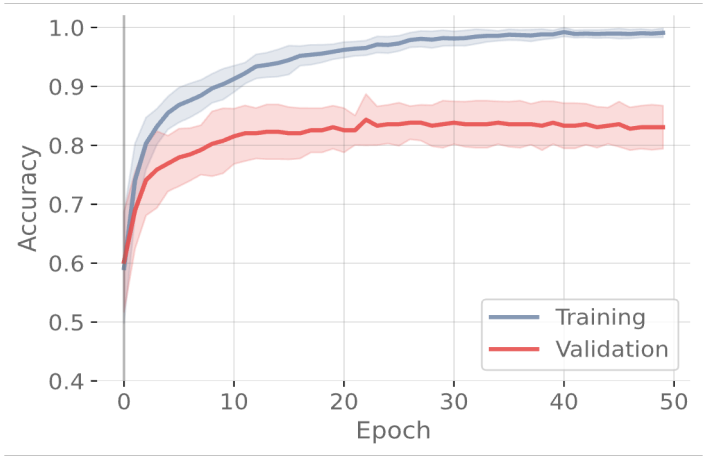
Uncertainty: $x^* = \text{argmin}_{x \in \mathcal{D}_{\text{Pool}}} \frac{|\bar{y}|}{\sqrt{v + \sigma_n{}^2}}$


Test accuracy as a function of dataset size for different AL acquisition functions, random, and upper-bound models

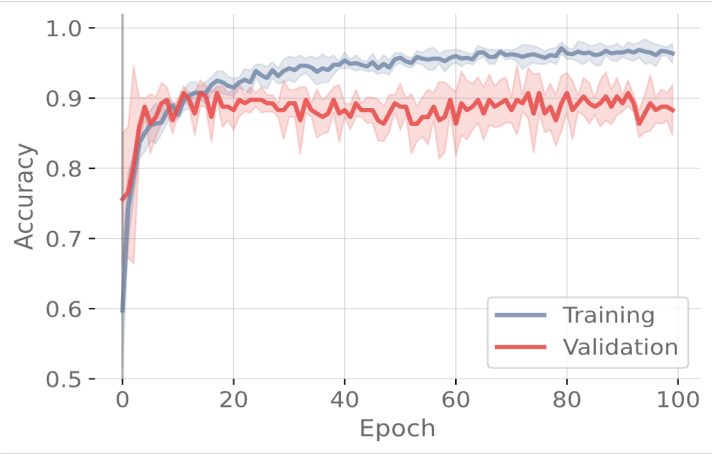
# Case study: Material transfer in composites manufacturing – Results




Randomly generated data

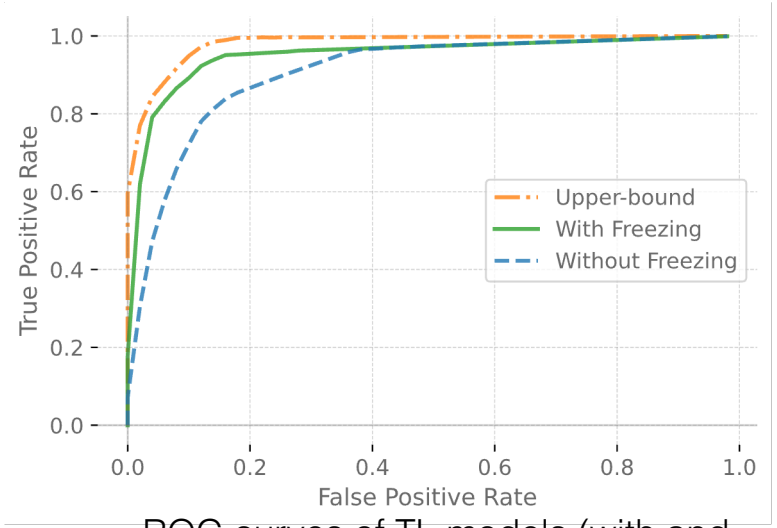



Active learning data




Active learning data + Transfer learning

| Model | Target Test Accuracy |
|---|---|
| Upper-bound | 94.64 % |
| **ATL** | **91.9 %** |
| TL | 87.88 % |
| AL | 86.2 % |
| Random | 80.08 % |




ROC curves of TL models (with and without freezing) and upper-bound model

# Summary and future work

- A **hybrid ML** framework composed of AL and TL is proposed.
- The proposed framework reduces the infeasible requirement of large data availability in advanced manufacturing for developing accurate learning models.
- **Uncertainty-based AL** approaches outperform random data collection in terms of model accuracy
- TL model equipped with **sequential unfreezing** and trained on **limited AL data** can dramatically improve the model accuracy and come very close to the performance of the upper-bound performance.

- An end-to-end **Bayesian Deep Learning** approach can be implemented to investigate the effectiveness of the ATL framework.
- Other acquisition functions and sampling method can be investigated.

# Program team

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Materials & Manufacturing Research Institute (MMRI)

MONASH University

## Industry 4.0

### AI development and digital integration

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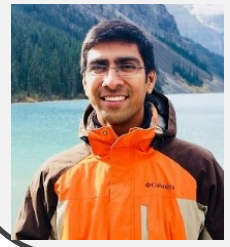
Monash University

Dr. Maryam Kamgarpour
UBC ECE

Dr. Apurva Narayan
UBCO CS



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A KOHLER COMPANY

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Mohammad Amin Roohi (Safe optimization)
Mohamad Khajezade (Few-shot learning)
Iman Jalilvand (Meta-reinforcement learning)
Hadi Hosseini (Control)
Debangsha Sarkar (Active learning)

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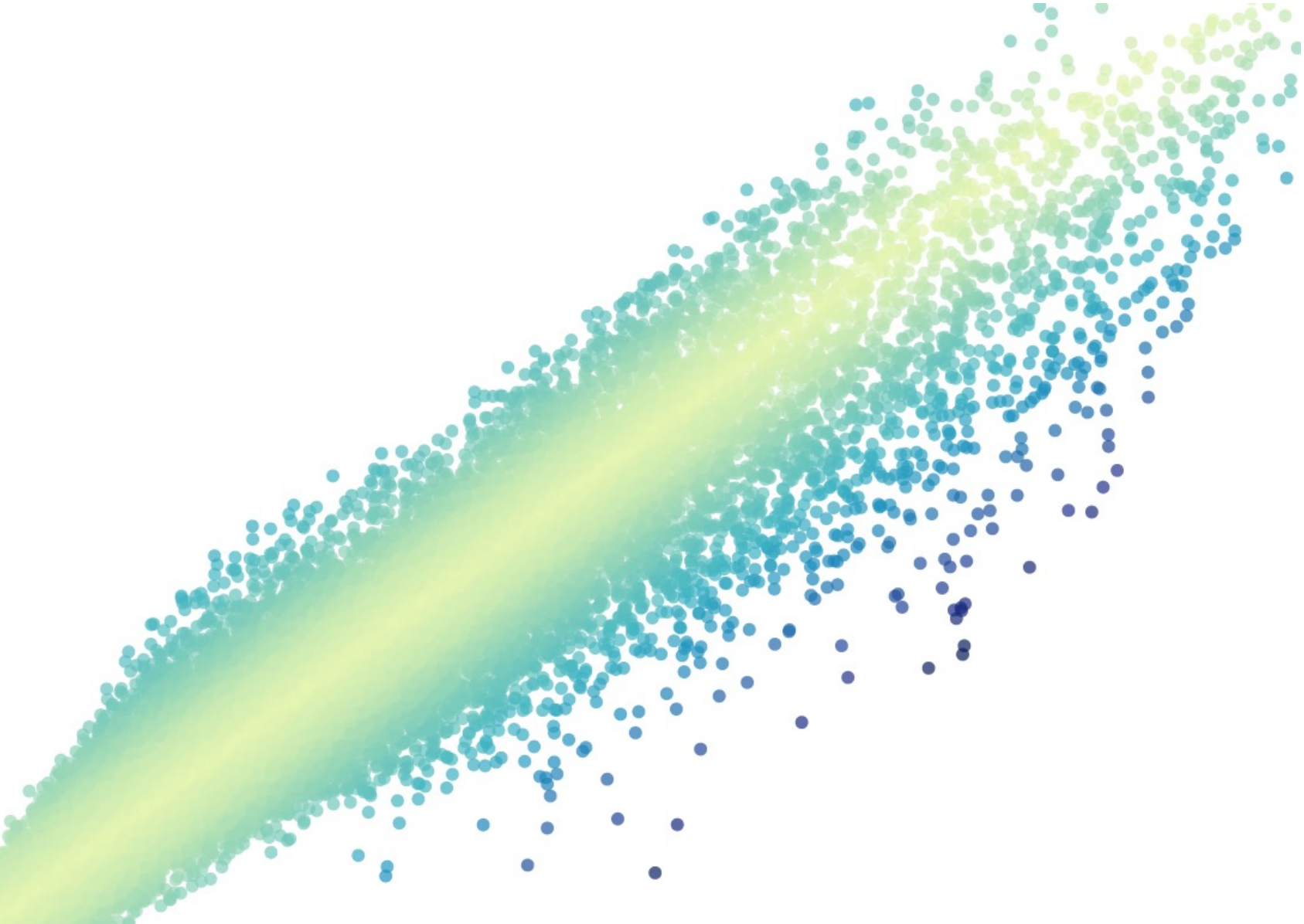

# Thank you