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

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The 4th IEEE International Conference on Industrial Cyber-Physical Systems
Victoria, Canada
May 10 -13, 2021
Content

Introduction and motivation
- 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

- Inventory and supply chain
- Equipment maintenance and monitoring
- Product quality and design

5 Vs of big data

- Volume
- Variety
- Velocity
- Veracity
- Value

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.

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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:

\[ p_{\text{training}}(x) = p_{\text{test}}(x) \]

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Motivation and research objective

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.

**Active Transfer Learning**
Transfer Learning

Conventional ML

Task A

model A

Task B

model B

Transfer Learning

Task A

Source

Knowledge transfer

Task of interest

Limited data

Task C

Target

model A

Trained using transfer learning

model C

Performance comparison

Performance

Training process

Sarkar et al 2018

Higher performance
increase slope

Higher asymptote

Better initial performance

Conventional learning

Transfer learning
Active Learning

• Closely related to Optimal Experimental Design
• Estimating the density function $P(y|x)$ with limited trials:
  
  o **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 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

\[ f = h \circ g \]
\[ f : \mathcal{X} \rightarrow \mathcal{Y} \]
\[ g : \mathcal{X} \rightarrow \mathcal{Z} \]
\[ h : \mathcal{Z} \rightarrow \mathcal{Y} \]
Case study: Material transfer in composites manufacturing – Problem statement

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
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.

<table>
<thead>
<tr>
<th>Input variables</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tool material</td>
<td>6061 Aluminum; AS4/8552 Composite; Invar 36; SAE 1020 Steel</td>
</tr>
<tr>
<td>Tool thickness (mm)</td>
<td>Min: 2.5, Max: 20</td>
</tr>
<tr>
<td>Part thickness (mm)</td>
<td>Min: 2.5, Max: 20</td>
</tr>
<tr>
<td>Heat rate – ramp 1 (°C/min)</td>
<td>1 to 5</td>
</tr>
<tr>
<td>Isothermal hold 1 (°C)</td>
<td>Min: 105, Max: 125</td>
</tr>
<tr>
<td>Heat rate – ramp 2 (°C/min)</td>
<td>1 to 5</td>
</tr>
<tr>
<td>Top-side HTC (W/m^2K)</td>
<td>Min: 10, Max: 125</td>
</tr>
<tr>
<td>Bottom-side HTC (W/m^2K)</td>
<td>Min: 10, Max: 125</td>
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</tbody>
</table>

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

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

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

**Knowledge transfer**

1. Source data (Abundant)
2. Target data (limited)
3. Active learning (GP)

Oracle (RAVEN)

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

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

**Methodology**

**Input variables**

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- 6061 Aluminum
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**Source data (Abundant)**

**Target data (limited)**

**Active learning (GP)**

**Source**

**Target**

**Knowledge transfer**

1. Source data (Abundant)
2. Target data (limited)
3. Active learning (GP)
Case study: Material transfer in composites manufacturing – Results

Gaussian Processes (GP) classification:

\[
p(y^*|x^*, X, f) \sim N(\hat{y}^*, \nu^*)
\]
\[
\hat{y}^* = K(x^*, X)[K(X,X) + \sigma_n^2 I]^{-1}y
\]
\[
v^* = K(x^*, x^*) - K(x^*, X)[K(X,X) + \sigma_n^2 I]^{-1}K(X,x^*)
\]

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):
\[
x^* = \arg\max_{x \in D_{Pool}} \nu
\]

Decision boundary:
\[
x^* = \arg\min_{x \in D_{Pool}} |\bar{y}|
\]

Uncertainty:
\[
x^* = \arg\min_{x \in D_{Pool}} \frac{|\bar{y}|}{\sqrt{\nu + \sigma_n^2}}
\]

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

<table>
<thead>
<tr>
<th>Model</th>
<th>Target Test Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper-bound</td>
<td>94.64 %</td>
</tr>
<tr>
<td>ATL</td>
<td>91.9 %</td>
</tr>
<tr>
<td>TL</td>
<td>87.88 %</td>
</tr>
<tr>
<td>AL</td>
<td>86.2 %</td>
</tr>
<tr>
<td>Random</td>
<td>80.08 %</td>
</tr>
</tbody>
</table>

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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Hadi Hosseini (Control)
Debangsha Sarkar (Active learning)
Acknowledgement

Research advisors:
• Dr. Abbas Milani
• Dr. Rudolf Seethaler

Advisors and colleagues at CRN and MMRI

Lead faculty researchers and colleagues in the NFRF project

Industrial, academic and funding partners:
Thank you