Machine Learning for 3D Printing Accuracy Control

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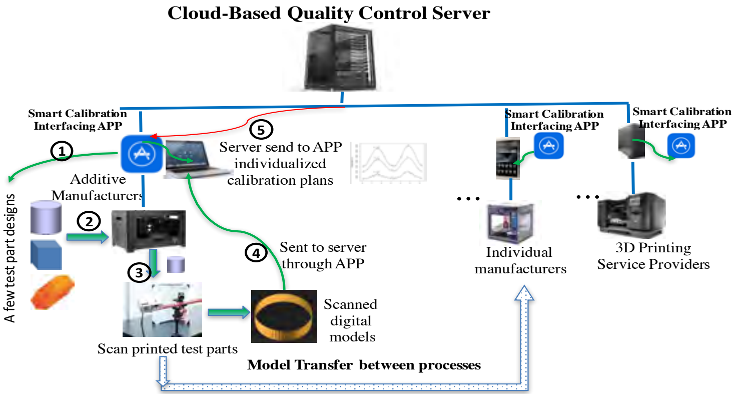
Machine Learning for Additive Manufacturing (ML4AM)

- Objectives: To learn, to predict, and to control shape accuracy based on 3D point cloud data
- Problem description and challenges
- ML4M: some problems and results
- Summary and future perspectives

Motivation: Cybermanufacturing



1. High-fidelity physical models: cost and uncertainties
2. Machine Learning: engineering-informed learning for the best use of data

ML4AM: Problem Description & Challenges

General description: given geometric (shape) measurement of AM built products under specific conditions, generate a model to predict and control shape deviations.

Challenges: shape and process complexities

- Shapes of AM built products: infinite variety
  [Kendall et al., 2009, Sharon and Mumford, 2006, Dryden and Mardia, 2016]

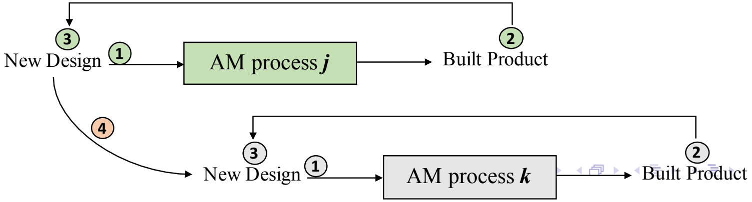
- Sample size of each shape: one-of-a-kind Mfg $(N \approx 1)$ vs. mass production $(N \approx \infty)$: AM often faces limited training samples for individual shapes.
- Process complexity: varying designs, building materials, and process conditions.

Questions of ML4AM

- How to address shape complexity issue?
- How to address process complexity issue?
- How to automate the process of learning heterogenous 3D printing data?

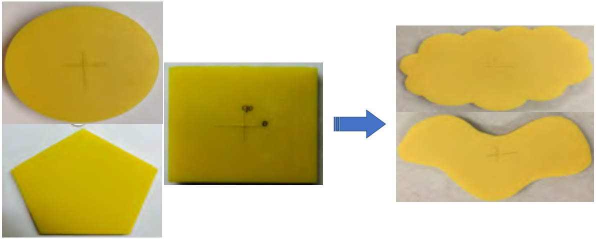
Offline AM Learning Problems

1. **Forward problem**: Learning for prescriptive prediction [Huang et al., 2015, Huang et al., 2014, Sabbaghi et al., 2014, Luan and Huang, 2017, Jin et al., 2016a]
2. **Inverse problem**: Learning for offline compensation of shape deviation [Huang, 2016]
3. **After-the-fact learning**: Learning for improved prediction of shape deviation [Sabbaghi et al., 2015, Sabbaghi et al., 2018]
4. **Transfer Learning problem**: model transfer from one process to another [Sabbaghi and Huang, 2016]



Offline ML4AM 1. Shape Heterogeneity: Prescriptive Modeling of Shape Deviations

Training shapes　　　　Freeform shapes

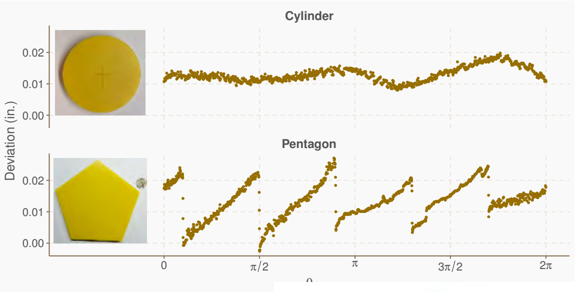


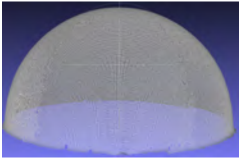
[Huang et al., 2015, Sabbaghi et al., 2014, Huang et al., 2014, Luan and Huang, 2017]

Key Ingredients of Prescriptive Modeling

- **Shape deviation representation to decouple shape complexity**

  [Huang et al., 2015, Huang et al., 2014]





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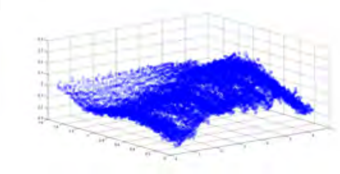
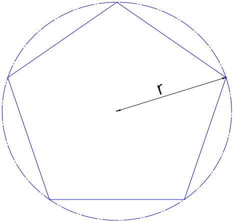


Key Ingredients of Prescriptive Modeling

- **Shape connection through cookie-cutter modeling framework**
  [Huang et al., 2014, Luan and Huang, 2017, Jin et al., 2016a, Jin et al., 2016b]
  A polygon can be viewed as being carved out from a circle, like cutting a cookie from a circular dough

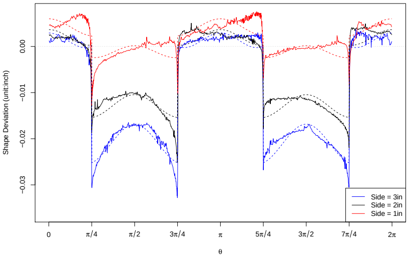


Example of In-plane Deviation Modeling

$$\Delta r(\theta, r_0(\theta)) = \overbrace{\beta_0 + \beta_1 cos(2\theta)}^{\text{cylindrical basis model } g_1(\cdot)} + \underbrace{\beta_2 sign[cos(n(\theta - \phi_0)/2)]}_{\text{cookie-cutter model } g_2(\theta, r(\theta))} + \varepsilon \quad (1)$$

- Orthogonal basis functions
- $n \longrightarrow \infty$, the polygon model approaches to the cylindrical model.

Regular Square Shape Shrinkage

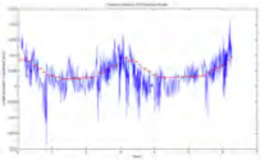


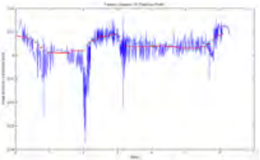
[Huang et al., 2014]

Learning for Freeform

Generalized cookie-cutter model: [Luan and Huang, 2015, Luan and Huang, 2017]

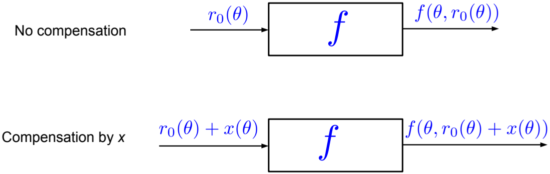
$$\Delta r(\theta, r_0(\theta)) = \underbrace{g_1(\theta, r_i(\theta_i))}_{\text{arcs of circular sectors}} + \underbrace{g_2(\theta, r_i(\theta_i))}_{\text{edges of polygons}} + \varepsilon \qquad (2)$$





(2). Learning for Offline Compensation of Shape Deviation

$x(\theta)$: amount of compensation applied to location θ
$r(\theta, r_0(\theta), x(\theta))$: actual profile after compensation $x(\theta)$
$r_0(\theta) + x(\theta)$: "nominal" profile with compensation $x(\theta)$



Connection with forward prediction model f:

$$\underbrace{r(\theta, r_0(\theta), x(\theta))}_{\text{Actual shape profile after compensation}} - \underbrace{(r_0(\theta) + x(\theta))}_{\text{New nominal input profile}} = f(\theta, r_0(\theta) + x(\theta))$$

The amount of compensation $x(\theta)$ can be learned.

Optimization for Learning: A Close-Form Solution

2D Optimal compensation $x^*(\theta)$ at each location θ as [Huang et al., 2015]

$$\mathscr{F}^{-1}(f(\cdot)) = x^*(\theta) = -\frac{\overbrace{f(\theta, r_0(\theta))}^{\text{shape deviation}}}{1 + \underbrace{\nabla f(\theta, r_0(\theta))}_{\text{deviation gradient wrp to r}}}$$

which minimizes the area deviation from its nominal shape.

3D Optimal compensation $x^*(\theta, \varphi)$ for shape deformation [Huang, 2016]:

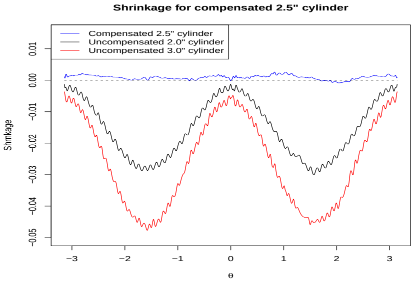
$$\mathscr{F}^{-1}(f(\cdot)) = x^*(\theta, \varphi) = -\frac{f(\theta, \varphi, r_0(\theta, \varphi))}{1 + \nabla f(\theta, \varphi, r_0(\theta, \varphi))} \tag{3}$$

which minimizes the volumetric deviation from its nominal shape.

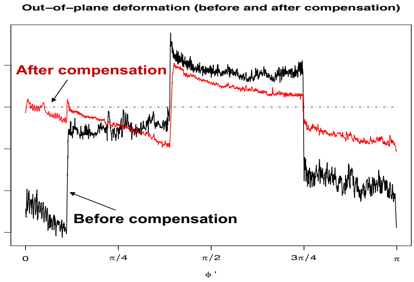
Experimental Validation for Compensation

Tested cylinder (90%), polyhedrons, and freeform shapes (>50%),

[Huang et al., 2015, Huang et al., 2014, Luan and Huang, 2017]



In-plane deviation compensation



Out-of-plane deviation compensation

(3). Bayesian Learning after the Fact

Motivation: After fabricating a product (w/wo optimal compensation), how could we learn from the observed data for model improvement? [Sabbaghi et al., 2015, Sabbaghi et al., 2018]

Bayesian learning of cookie-cutter model:

- Cookie-cutter modeling framework [Huang et al., 2014], and

$$\Delta r(\theta, r_1(\cdot)) = g_1(\theta, r_0) + g_2(\theta, r_1(\cdot)) + \varepsilon_\theta$$

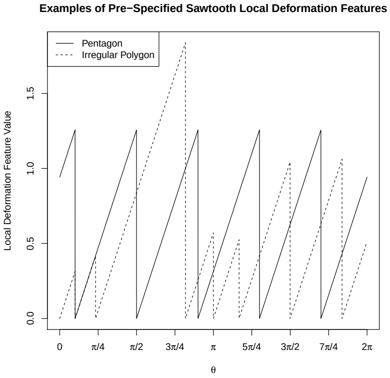
- Bayesian posterior predictive checks [Gelman et al., 1996; Gelman, 2003].

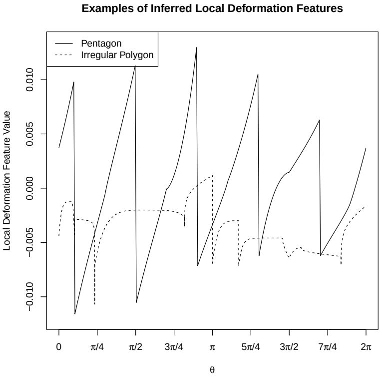
$$\Delta r(\theta, r_1(\cdot)) - g_1(\theta, r_0).$$

This discrepancy measure [Meng, 1994] can illuminate parsimonious specifications for g_2.

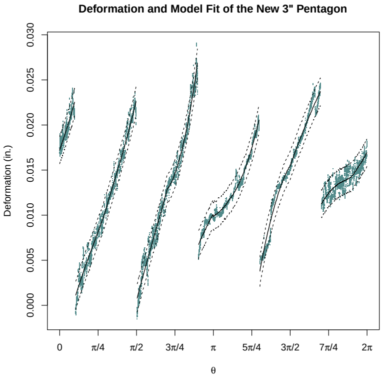
Learning Cookie-Cutter Model

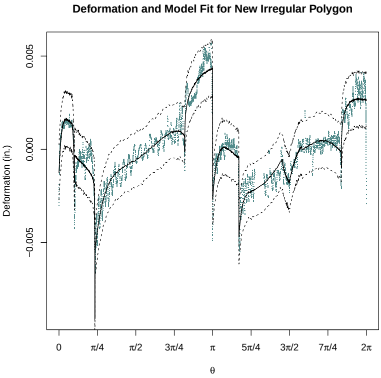
- Keep cylindrical basis g_1 and learn cookie-cutter function $g_2(\cdot)$
- Improved cookie-cutter model $g_2(\cdot)$ applicable to freeform shapes





Improved Model Prediction

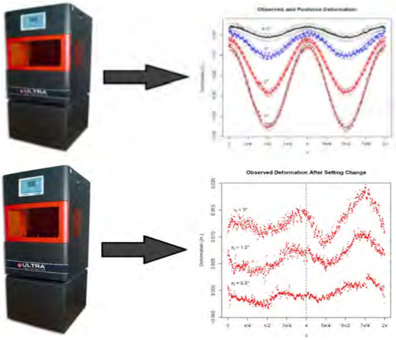


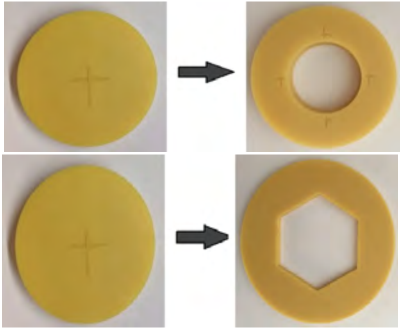


(4) Process Heterogeneity: Model Transfer Based on Effect Equivalence

Condition-induced process changes

Design-induced process changes

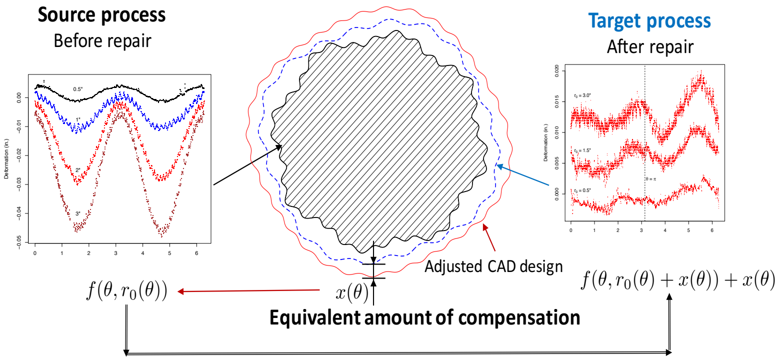




How can we transfer the model to the new process condition/environment without repeating previous procedures, particularly for cybermanufacturing?

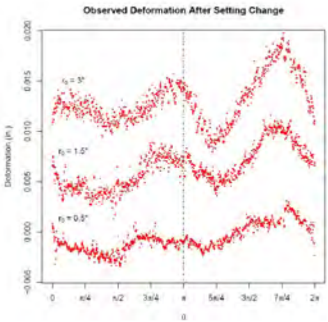
Key Idea of Model Transfer: Effect Equivalence Principle

Target process: "Nominal" shape (cylinder) printed in a "new" process
Source process: "Actual" shape printed in a "old" process
Transfer link: "Compensated shape" to obtain the "nominal" shape by the "old" process



[Wang et al., 2005, Wang and Huang, 2006]

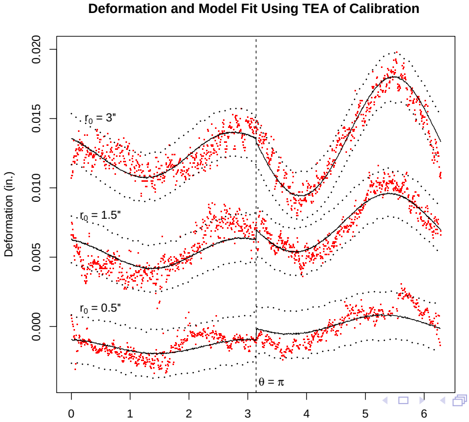
Mean Effect Equivalence of Calibration and Compensation



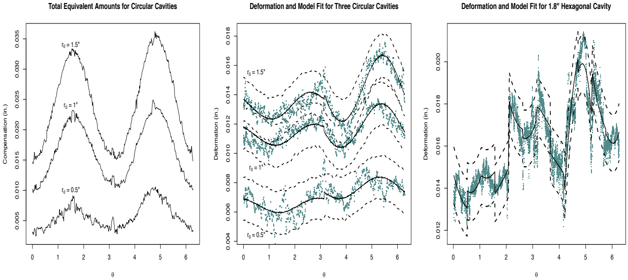
$$\int_{-\infty}^{\infty} y p(y \mid \mathbf{z}, x_1, x_2, \psi) dy = \int_{-\infty}^{\infty} y p_1(y \mid \mathbf{z}, T_{2\rightarrow 1}(x_1, x_2), \psi_1) dy$$

Model Transfer Via TEA

$$\Delta(\theta, x_1, x_2) = f(\theta, T_{2\rightarrow 1}(x_1, x_2)) + \varepsilon_\theta.$$



Model Transfer for Different Shapes [Sabbaghi et al., 2018]



Automated Machine Learning (Ferreira, Sabbaghi, Huang; 2017)

Model Guided Neural Network Structure Design (Ferreira, Sabbaghi, Huang; 2017):

1. For a baseline shape s printed under a particular 3D printing process p,

$$\mathbf{y}_{s,p} = \mathbf{H}_{s,p}\boldsymbol{\beta}_{s,p} + \boldsymbol{\varepsilon}_{s,p}.$$

2. For shape s printed under a new 3D printing process p',

$$\mathbf{y}_{s,p'} = \mathbf{H}_{s,p'}\boldsymbol{\beta}_{s,p} + \mathbf{H}_{s,p'\to p}\boldsymbol{\beta}_{s,p'\to p} + \boldsymbol{\varepsilon}_{s,p'}.$$

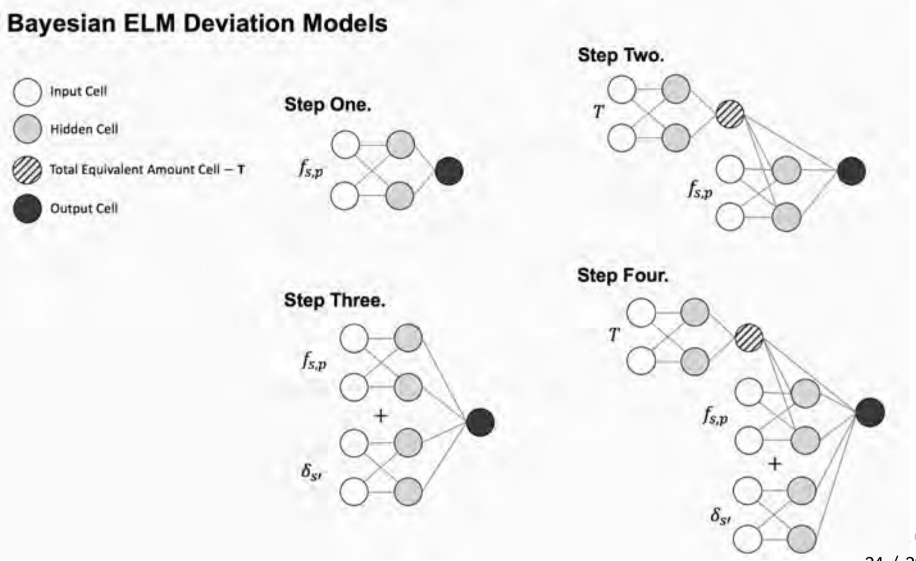
3. For a new shape s' printed under the 3D printing process p,

$$\mathbf{y}_{s',p} = \mathbf{H}_{s,p}\boldsymbol{\beta}_{s,p} + \mathbf{H}_{s',p}\boldsymbol{\beta}_{s',p} + \boldsymbol{\varepsilon}_{s',p}.$$

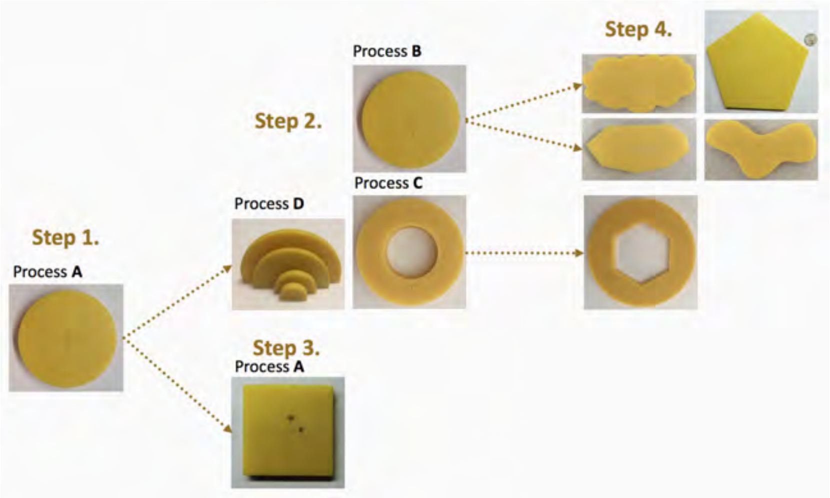
4. For a new shape s' printed under a new 3D printing process p',

$$\mathbf{y}_{s',p'} = \mathbf{H}_{s,p'}\boldsymbol{\beta}_{s,p} + \mathbf{H}_{s,p'\to p}\boldsymbol{\beta}_{s,p'\to p} + \mathbf{H}_{s',p'}\boldsymbol{\beta}_{s',p'} + \boldsymbol{\varepsilon}_{s',p'}.$$

Four-Step Model Building Approach

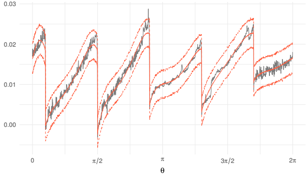


Case studies overview

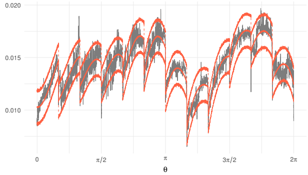


Transfer Model to New Shape and Process

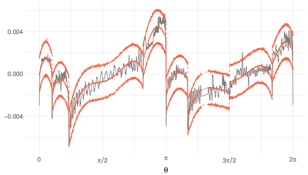
Combine Steps 2 and 3 to transfer $f_{s,p}(\cdot)$ to **new** shape s' manufactured under **new** process p' – $f_{s',p'}(\cdot)$.



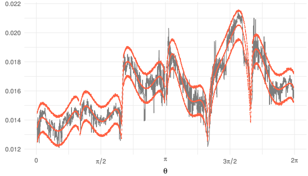
(a) *Pentagon*



(b) *Dodecagon*



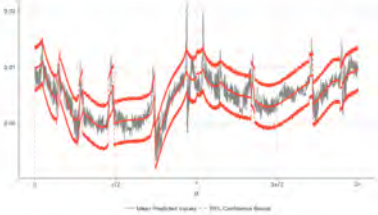
(c) *Irregular polygon*

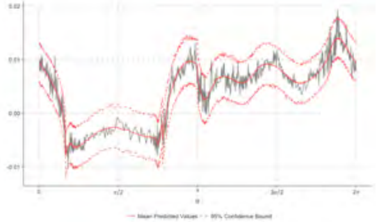


(d) *Inner hexagon*

Transfer Model to New Shape and Process

transfer $f_{s,p}(\cdot)$ to **new** shape s' manufactured under **new** process p' – $f_{s',p'}(\cdot)$.



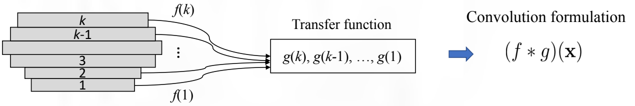


Summary and On-going ML4AM Work

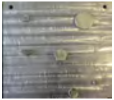
- Established model-guided, automated Machine Learning of shape data for deviation control in 3D printing
- Addressed heterogeneity issues due to shape and process complexities

On-going Work:

- Engineering-informed convolution framework for learning 3D shapes [Huang et al., 2018]



- Laser Powder Bed Fusion (LPBF) process [Luan et al., 2018]



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Prof. F. Tsung at HKUST; Prof. B. Colosimo at Politecnico di Milano, Italy
Prof. M. Plumlee, Northwestern University; Prof. H. Wang, Florida State University
Industry: HP Labs at Palo Alto and Honeywell Aerospace

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