Spatiotemporal Data Analytics in 3D Printing Quality Prediction

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Presenation Outline

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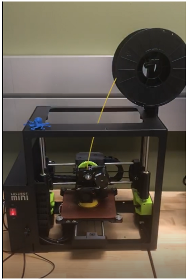
Benefits

- can directly build geometrically complex products with computer control
- less material and lower cost than traditional manufacturing methods



Problem Description

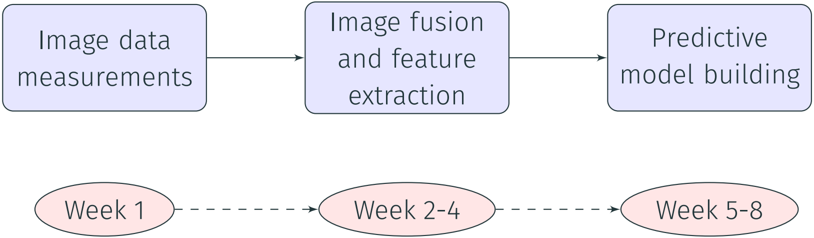
An optimization bottleneck

Material solidification in the printing process yields geometric shape deviation.
Traditionally, this problem is solved by manual inspection - works but **inefficient**.

Objectives

- Develop methods to extract spatiotemporal patterns from the measurement images to characterize printed parts quality
- Build a predictive model for part quality given process parameters

Project Timeline



Preliminary Work

- Image data measurements.

Use Keyence VR-3000 Wide-Area 3D Measurement system to measure the parameters from the surfaces of the 3D-printing object.

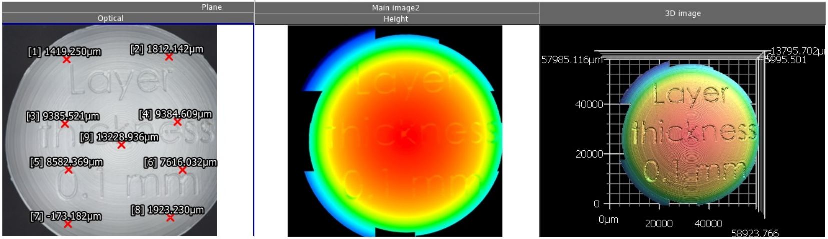


Figure 1: Measurement of point height of a dome object of layer thickness 0.1mm

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Disadvantage: the features might be incomprehensive

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Advantage: comprehensiveness
Disadvantage: not really interpretable

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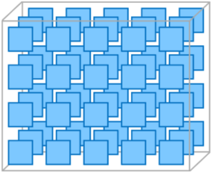

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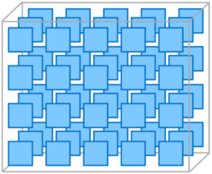

Figure 2: rank 3 tensor

- **Tensor Decomposition**: any scheme for expressing a tensor as a sequence of elementary operations acting on other, often simpler tensors.

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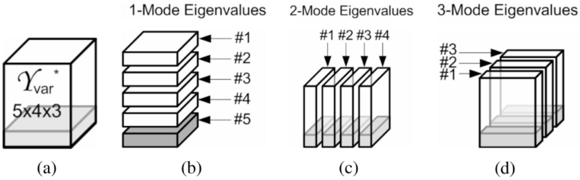
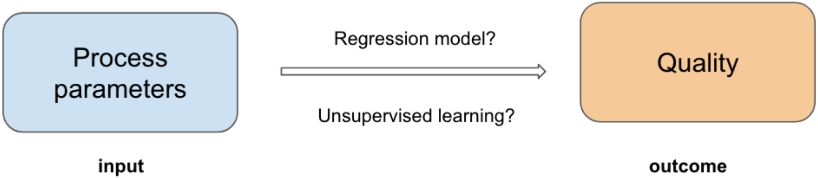
  Limitation: fails to take into account the spatial correlation of the image pixels within a localized neighborhood.
- MPCA: a multilinear algorithm performing dimensional reduction in all tensor modes seeking those bases in each mode that allow projected tensors to capture most of the variation present in the original tensors.



Visual illustration of (a) total scatter tensor, (b) 1-mode eigenvalues, (c) 2-mode eigenvalues, and (d) 3-mode eigenvalues.

Predictive Model



Potential Challenges

- Unique sample, not many references to compare

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References

- MPCA: Multilinear Principal Component Analysis of Tensor Objects
  https://ieeexplore.ieee.org/document/4359192/
- Image Fusion Using Tensor Decomposition and Coefficient Combining Scheme
  http://www.ijettjournal.org/volume-15/number-9/IJETT-V15P286.pdf