The Consortium for Enabling Technologies and Innovation

Virtual Summer Meeting for Young Researchers

Additive Manufacturing Signature Analysis

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National Nuclear Security Administration

Outline

Background

- Additive manufacturing
- Proliferation risk
- Steps for a solution
- Current work
  - Temperature data
  - Position data
- Planned work
  - New instrumentation
  - Collaboration with Los Alamos National Laboratory

Background

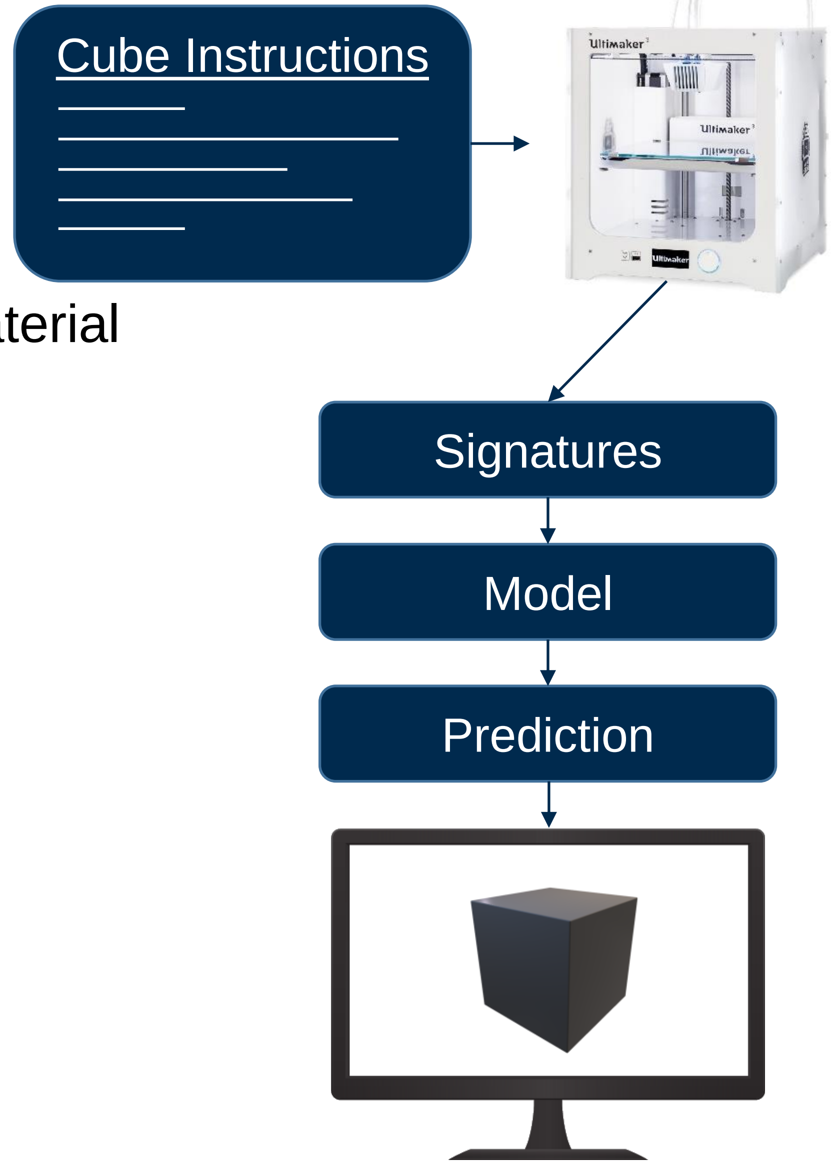
What is Additive Manufacturing?

- Building a component by placing down material
- A set of instructions are needed to know where to place material

Signatures can be drawn from additive manufacturing processes

- Temperature around the print can change
- Machine causes vibrations
- Microphones can listen to sounds generated by motors
- These signatures be **correlated with instructions**

Proliferators can use that correlation to predict instructions → reverse engineer a component



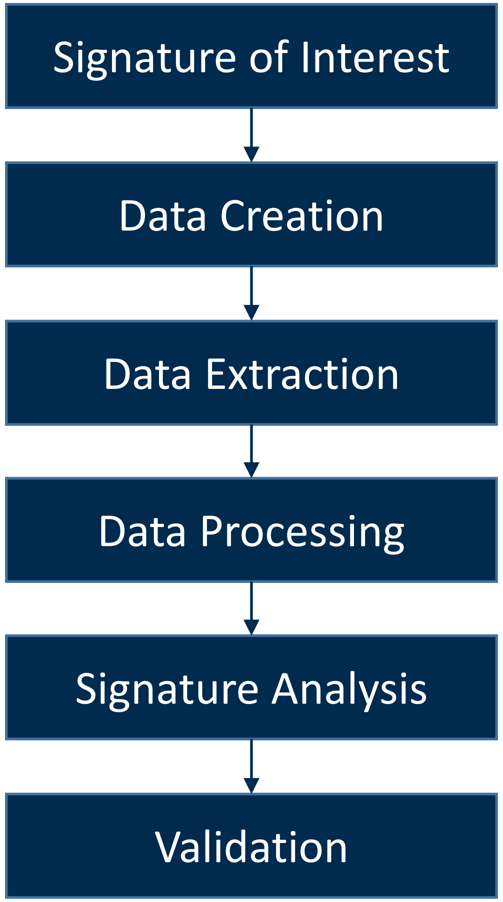
Problem Statement

Nuclear Nonproliferation Applications

- Lead to preventative measures:
  - Protect nuclear component blueprints
  - Protect small arms blueprints, etc.
- This work could lead to remote monitoring technologies
  - Learn exactly what a proliferator is printing
    - Material
    - Geometry

What steps do we need to perform to find a solution?

- Decide on signature of interest (side channels)
  - i.e. Temperature, Current, Vibration, etc.
- Dataset creation
- Method for Data extraction/formatting
- Validate if signature would give us useful information



Data Creation

Geometries Used:

- Cube
- Cylinder
- "Buzz" Georgia Tech Mascot (not attempted yet)

Dimensions:

- Cube: x = 1cm, y = 1cm, z = 1cm
- Cylinder: r = .5cm , z = 1cm
- "Buzz" Georgia Tech Mascot (N/A)

Material/Process Specifications:

- Ultimaker PLA
- 4mm nozzle
- .1mm layer height

System: Ultimaker 2+

Data Extraction/Processing

Develop a reliable method for data extraction

Data of Interest (currently)

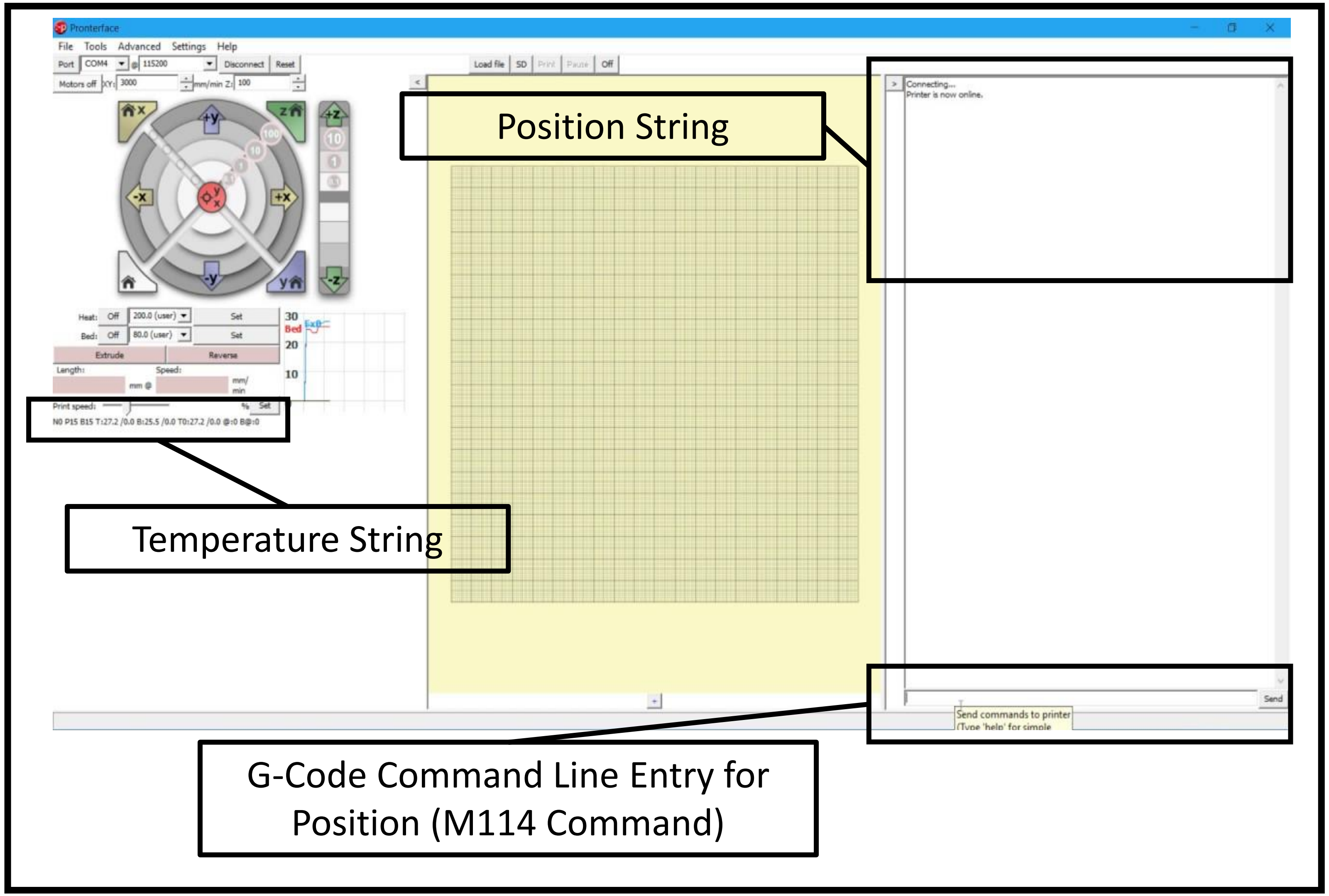
- Position (XYZ)
- Temperature

Ultimaker 2+ sensors

Pronterface software

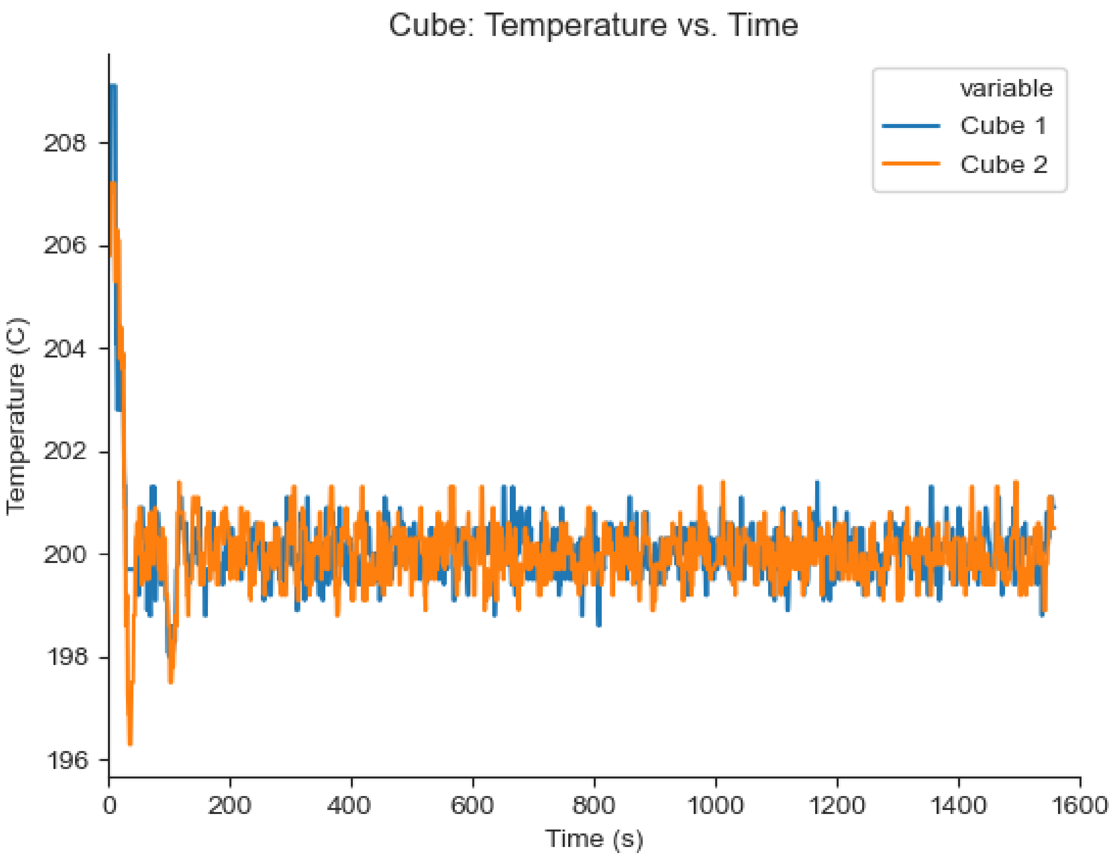
Python script for parsing of temperature and position strings

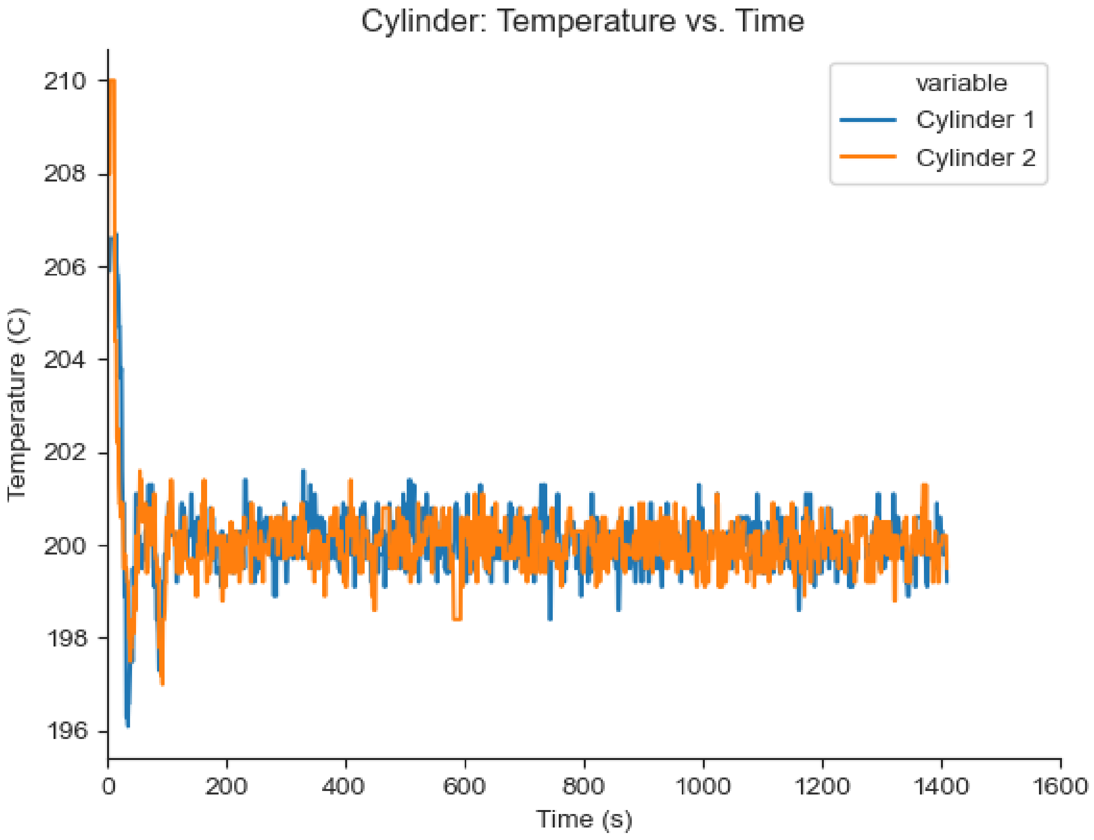
Python script for formatting data



Temperature Data

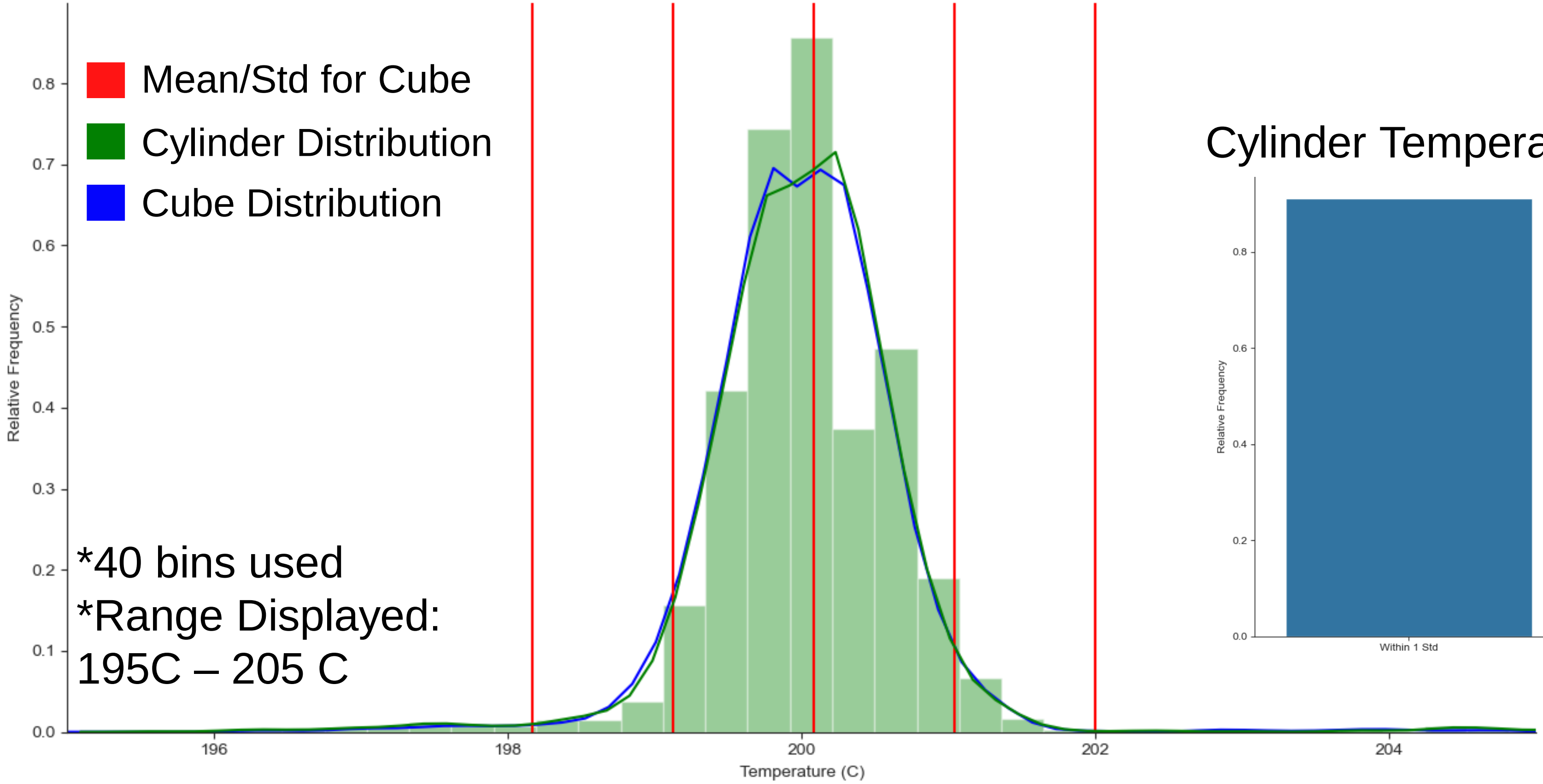
Temporal Temperature Distributions



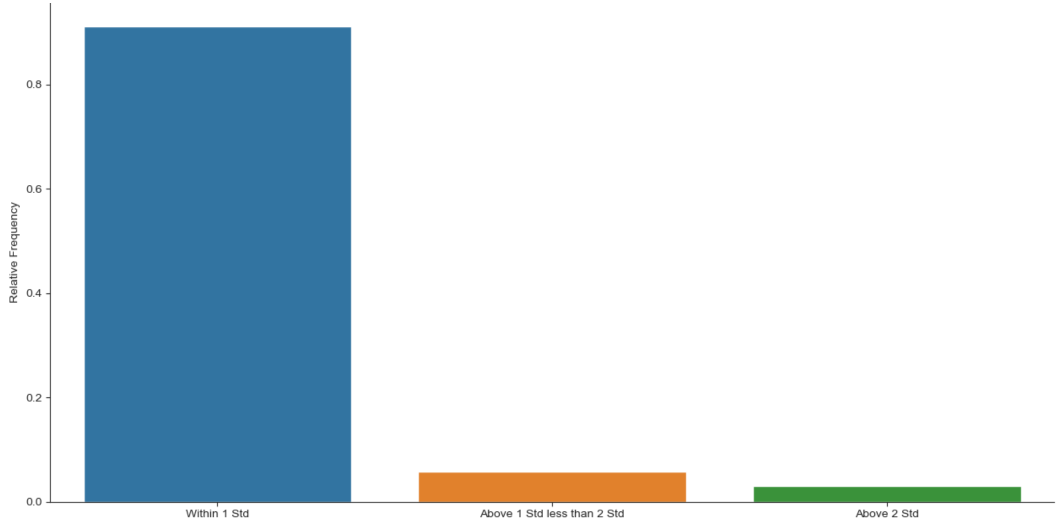


Temperature Data

Cube vs. Cylinder Temperature Distribution



Cylinder Temperature Distribution Relative to Cube



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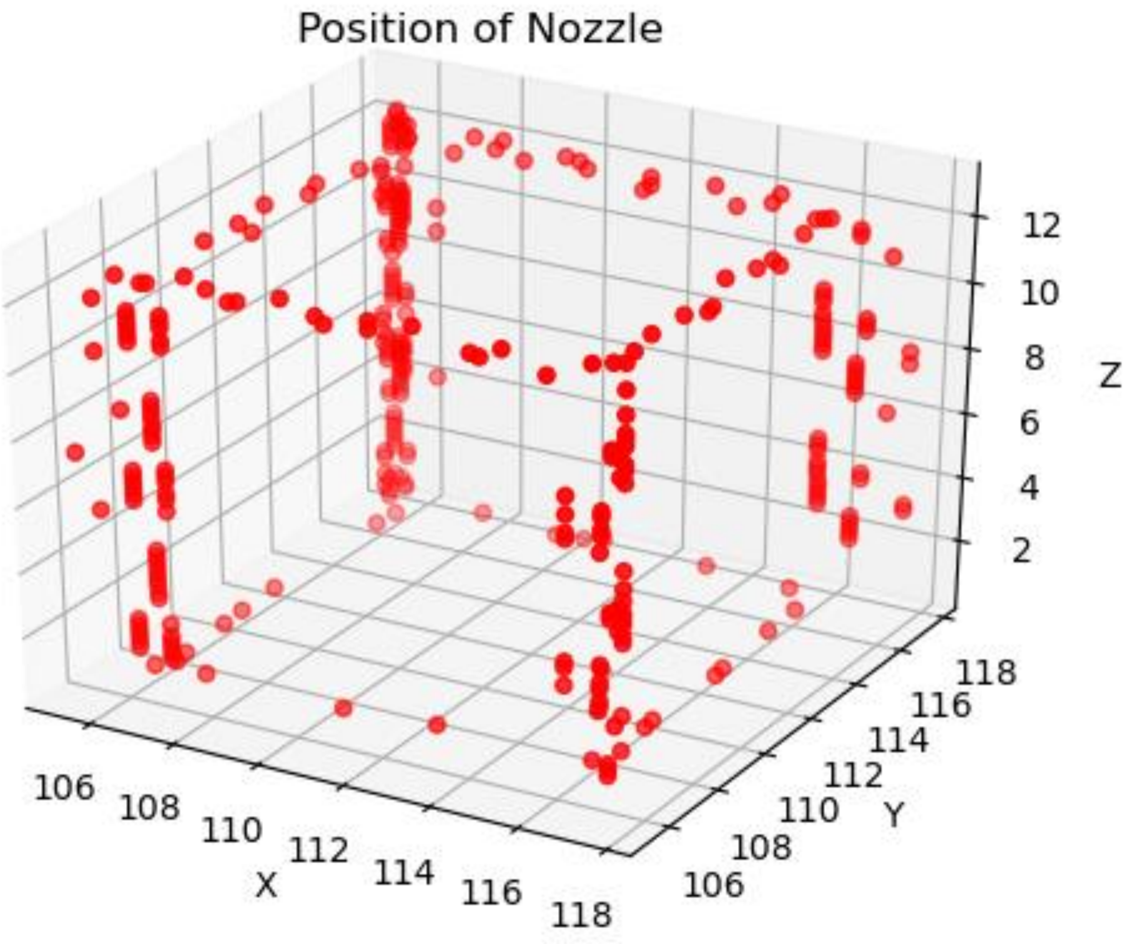
Position Data



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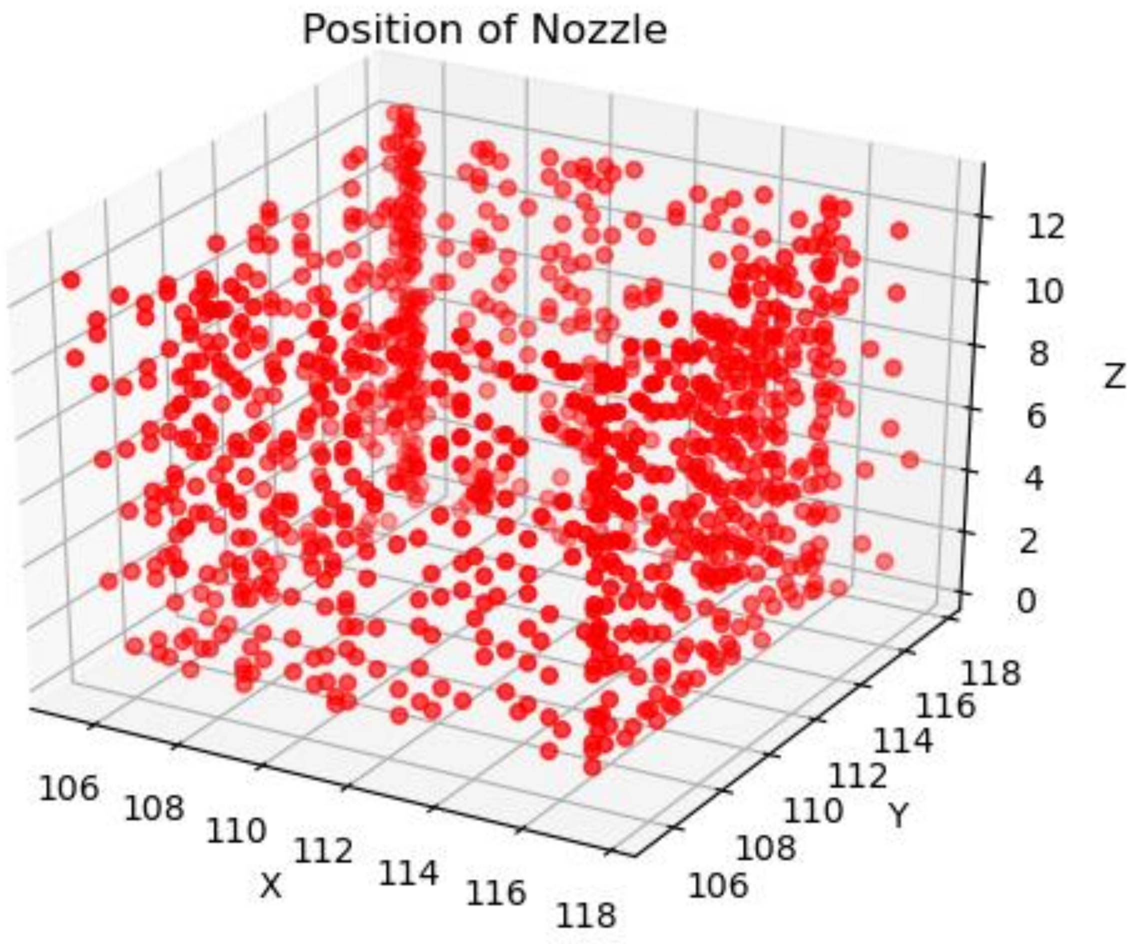

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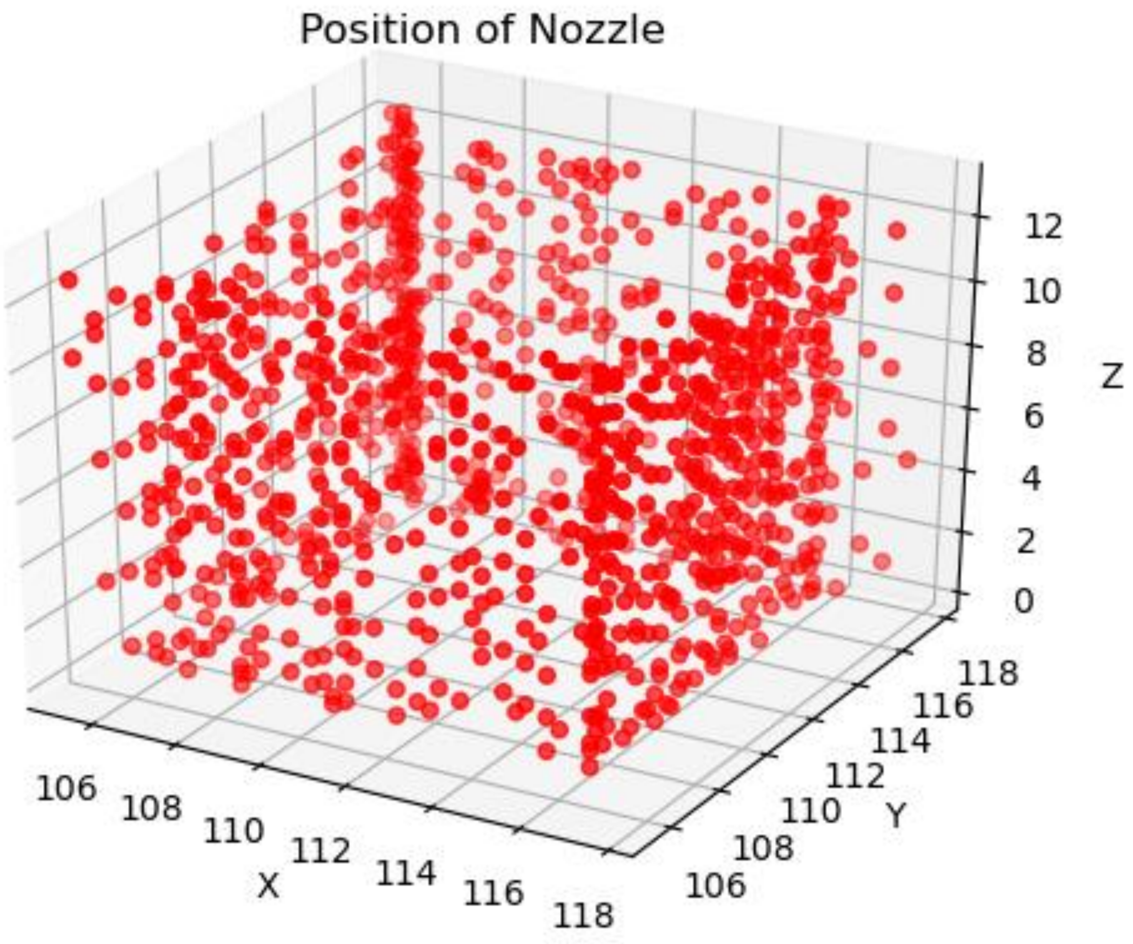
Position Data



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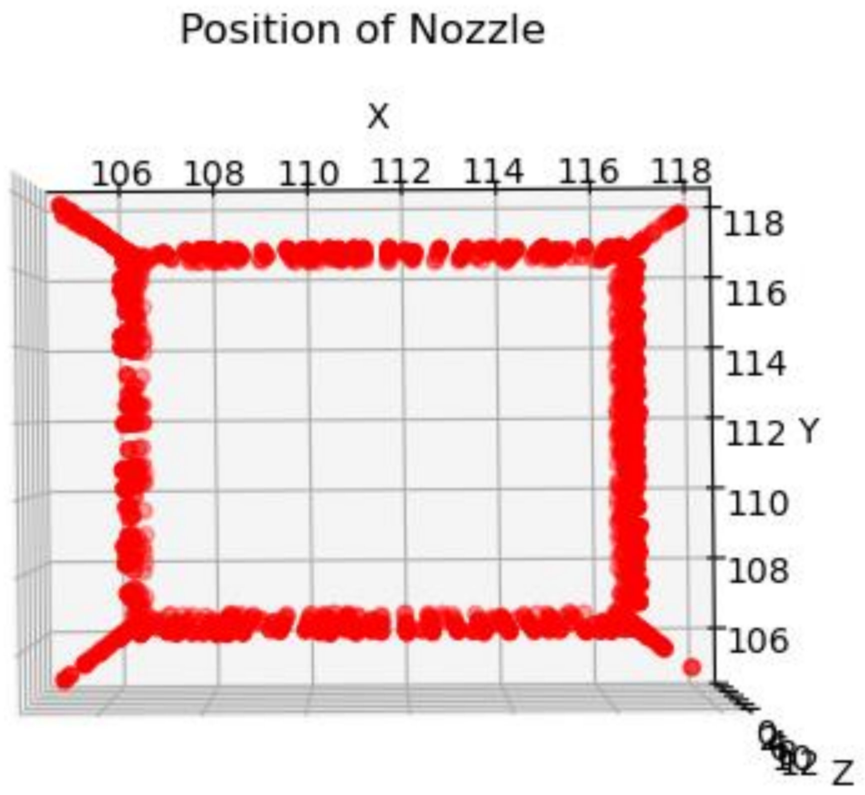

100% Infill Top View

Challenges Faced

Low sampling rate

- Positional data was only able to be obtained every 4 seconds (1 sample/~4 seconds)
- Temperature data in Pronterface only updated once every second (1 sample/second)

G-code could not run concurrently

- i.e. requesting position while printing had a lot of latency
- Lead to a lot of inconsistency when collecting position data

Could not collect position data for infill (bulk material)

With data collected there was no discernable pattern at first glance

Leads to next phase: Better Instrumentation/Data Extraction

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Next Phase

Instrument the ultimaker with better sampling systems

Implemented with National Instruments

- Bypass Pronterface software
- New Sensors (Acoustic and Vibration, Current, and Temperature)
- Faster Sampling rates (~90 samples/s)
- Labview can export files of signature histories
- Time synced

Challenges

- Appropriate Mounting
  - Vibration sensor (bench vs. Ultimaker Frame?)
  - Thermocouple embedment?
    - Replace Thermocouple in Utlimaker 2+

Next Next Phase

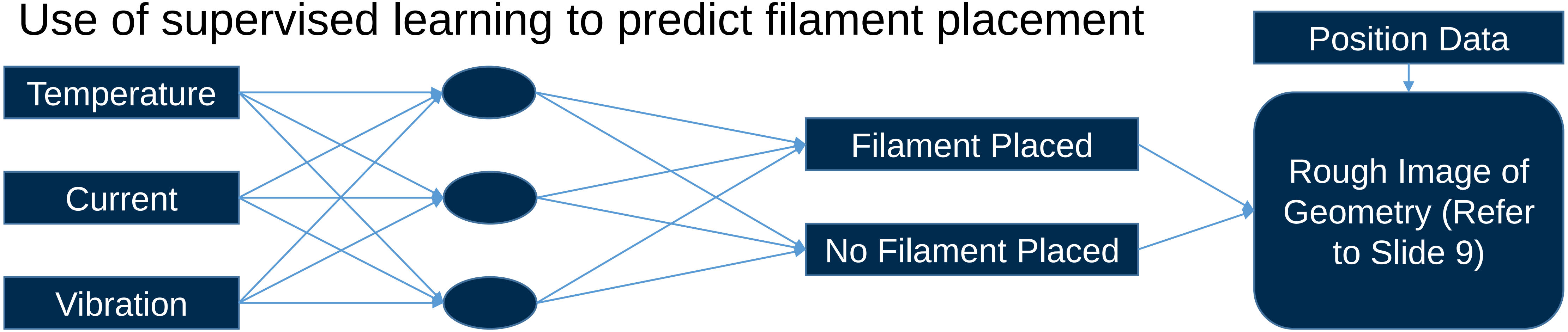
Take data samples and perform statistical analysis on each signature

- Compare distributions of geometries once again

Possible use of k-nearest-neighbor classifier

- To see if signatures from different geometries correlate
- Individual signatures
- All signatures

Use of supervised learning to predict filament placement

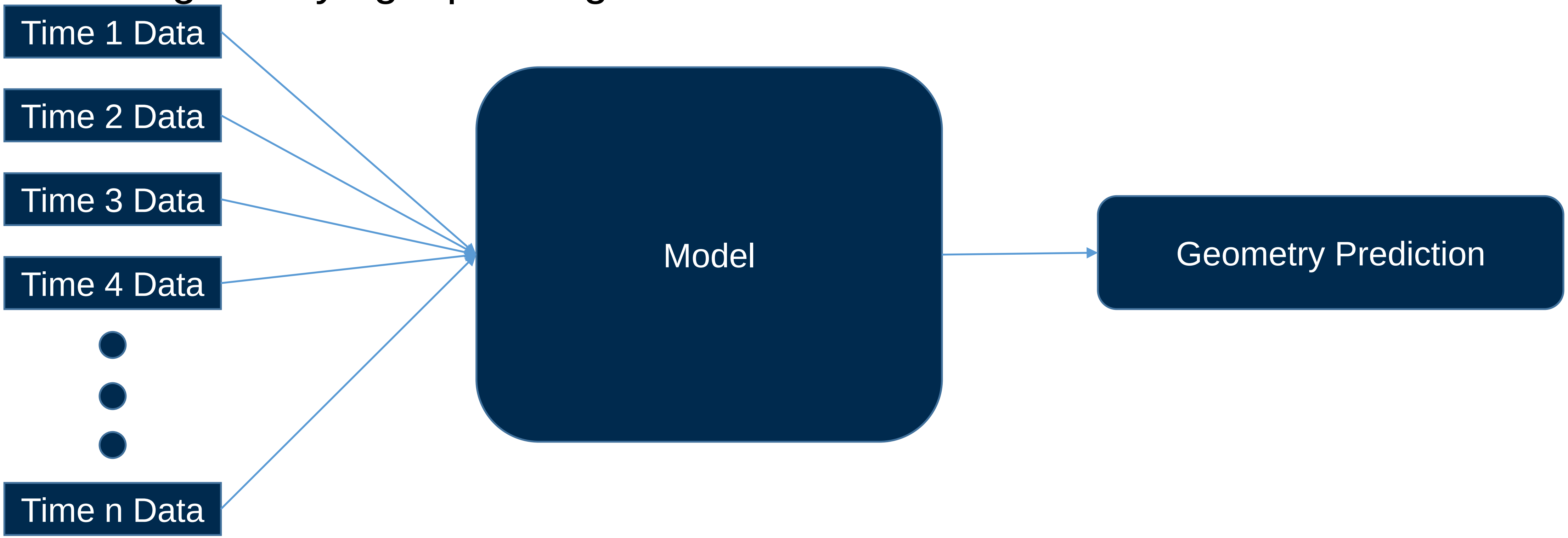


Next Next Phase

Incorporation of time-based data

- Predict overall geometry
- Predict geometric features (flat surfaces, curves, jagged edges, etc.)

Challenge: Varying input length



Metal Additive Manufacturing

So far, my work has involved thermoplastics…

I will be working with Los Alamos National Lab Sigma Division

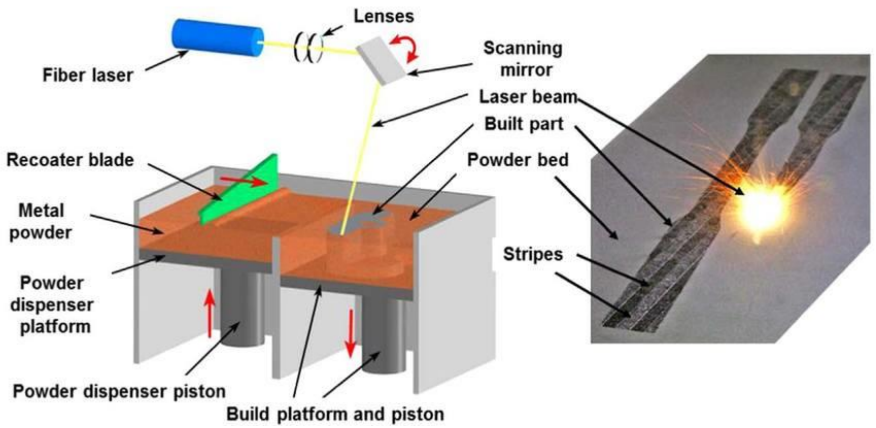
- Laser Powder Bed Fusion Group
- Metal additive manufacturing

Goal is to characterize the circumstances surrounding defect formation

- Relation to quality control for additive manufacturing

Collaboration

- Los Alamos National Lab is providing data
- My job is to process that data and find/affirm patterns



[1] Laser Powder Bed Fusion System

Metal Additive Manufacturing

LANL will be sending large datasets initially

Data processing:

- **EOS GmbH** Electro Optical Systems Software for interpreting
- Allows for filtering of the data before extraction
  - i.e. only extracting thermal data above/below a certain threshold
  - Filtering will provide multiple ways to view the same data

Machine Learning:

- Use of Sklearn Python library for K-means clustering
  - Defects may have similar characteristics to each other
  - May possibly be used for labeling data for use in neural networks
- Pytorch Python library for neural networks
- Computational Resources
  - Currently investigating what resources (clusters are available)

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References

[1] Laser Powder Bed Fusion of Nickel Alloy 625: Experimental Investigations of Effects of Process Parameters on Melt Pool Size and Shape with Spatter Analysis - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/The-laser-powder-bed-fusion-system-Direct-Metal-Laser-Sintering-by-EOS-GmbH_fig1_315441121 [accessed 29 Jun, 2020]

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