

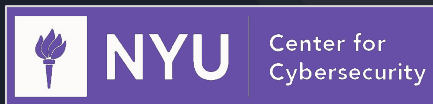
## **Threat Vector Analysis - Finding Fault in the Pile**

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I am a Senior in mechanical engineering at the New York City College of Technology in Brooklyn New York. Over the past three years, I have worked with my school and several others both inside and outside of the US in order to research and learn more about Additive Manufacturing and how it is incorporated with the engineering supply chain and design process. This includes working with NYU over the summer as part of their NSF IRES summer research program with students from India to learn how cyber security plays a role in AM and how machine learning can be used to combat cyber/physical attacks,

# Threat Vector Analysis - Finding Fault in the Pile

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## Background

In the additive manufacturing (AM) supply chain, there are numerous factors that may allow malicious third parties to negatively influence the specific outcomes of a given product. These factors are known as threat vectors, and commonly include avenues for counterfeiting, information leakage, and sabotage.

For AM one such case where this applies is with G-Code files, and through machine learning, malicious files can be detected through feature recognition seeing how the altered ones deviate from the acceptable ones thus finding the fault(s) in the pile.

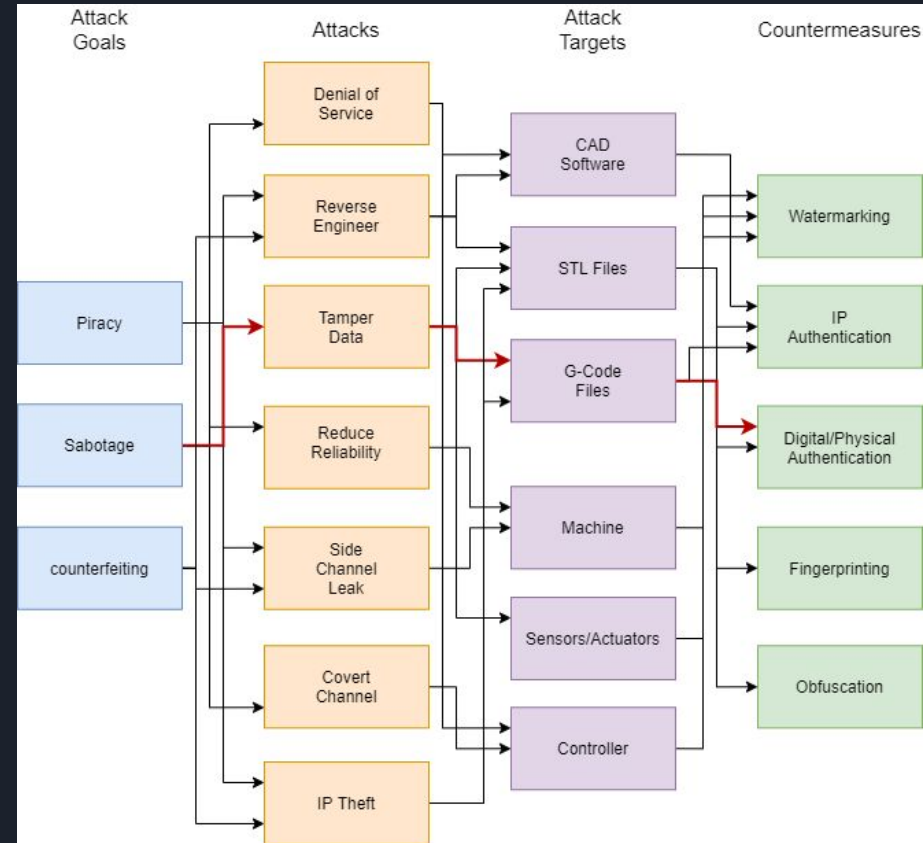


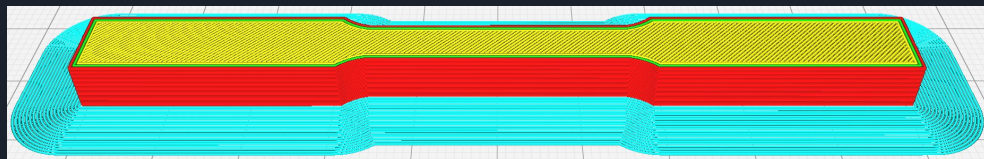
Figure 1: Threat vectors in additive manufacturing

## Method of Attack

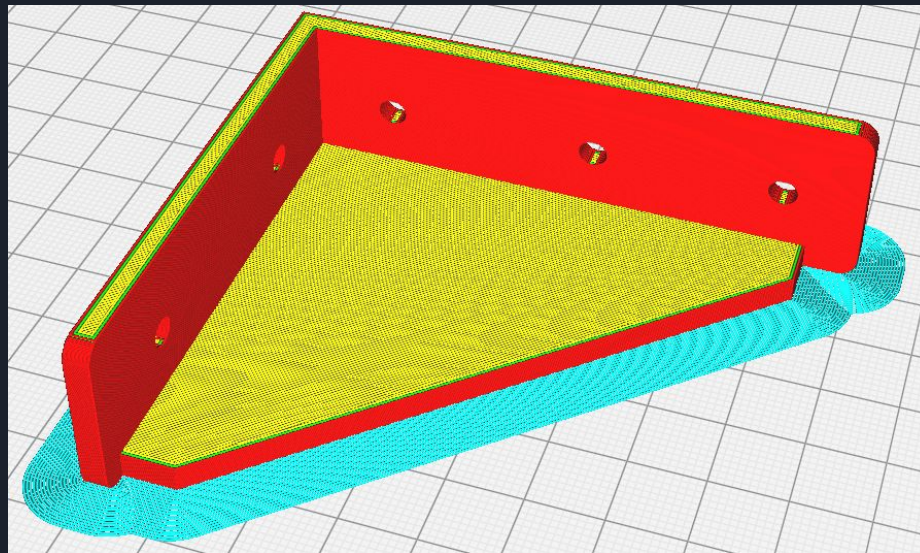
Two data sets of g-code files were prepared for the students to examine and find the defected files within.

The first dataset was composed of 180 files, two of which were compromised. The files were each rotated 1 degree from the original starting point about the Y-axis.

The Second dataset was composed of 4230 files, 60 of which were compromised. The model used was a bracket sliced in Ultimaker Cura.



*Figure 2. Tensile test specimen*

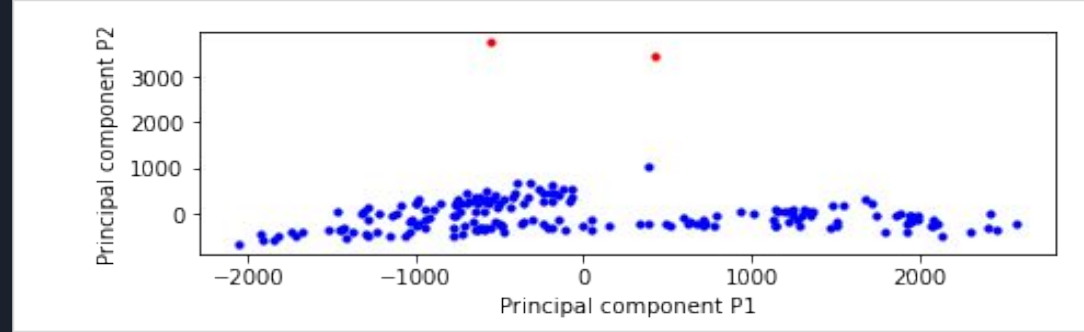


*Figure 3. Bracket*

## Fault in the pile 180 codes



Figure 4. Scatter plot for Gcode showing principle component outliers



Three methods were created to find the faulty files:

- Statistical Analysis Approach:** Broke the G-code into the individual commands and examined the count of each command as well as the decimal range of each input associated with the command.
- Machine Learning Approach:** Used python to break down the data set and then performed principal component analysis to cluster the files to find outliers.
- Combination Method:** Examined the files in much of the same way as the first two methods, finding the faulty files statistically and validating the files with machine learning using DBSCAN.

## Fault in the pile 4320 codes

- Pure statistical analysis method was able to flag 50 files as potentially tempered. 29 of these files were shown to be correctly identified, and 21 were false positives.
- Pure machine learning method only detected 35 files, where 28 of those were correctly identified.
- Combined method detected 50 files correctly, DBSCAN validated the found files and ruled out potential false flags.

Overall 50 out of the 60 damaged files were found.

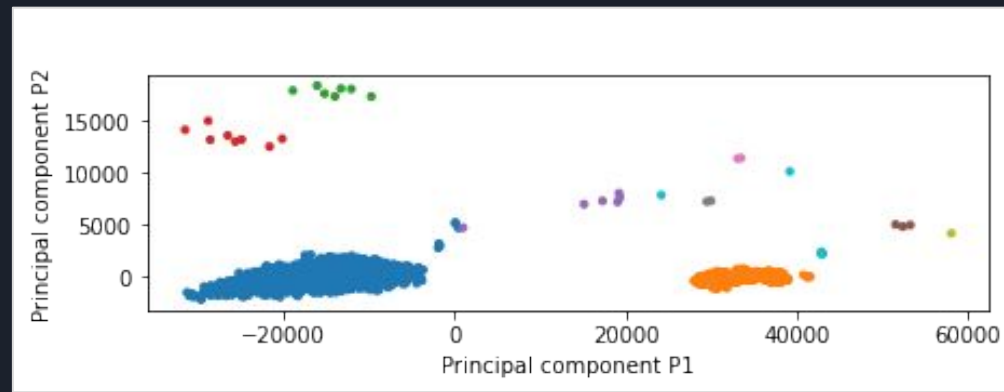


Figure 5. Principal component break down for sample set of 4320 files

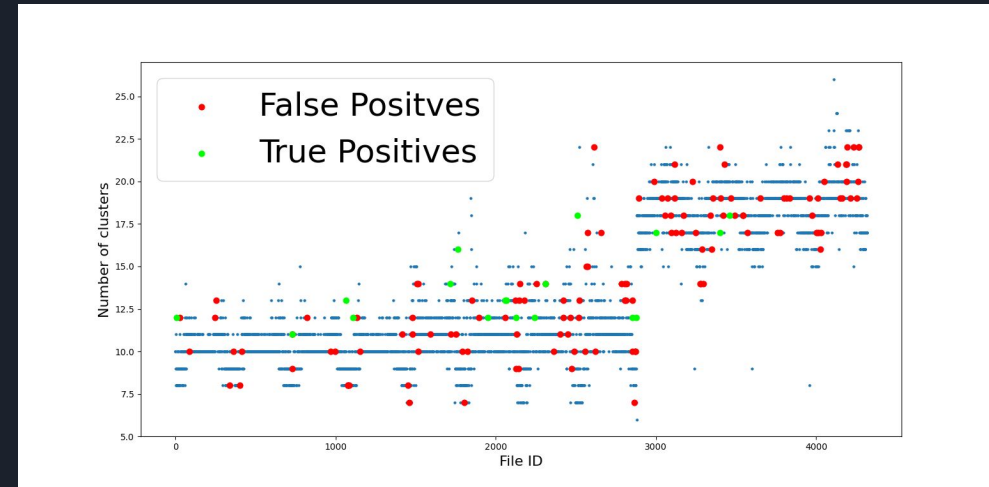
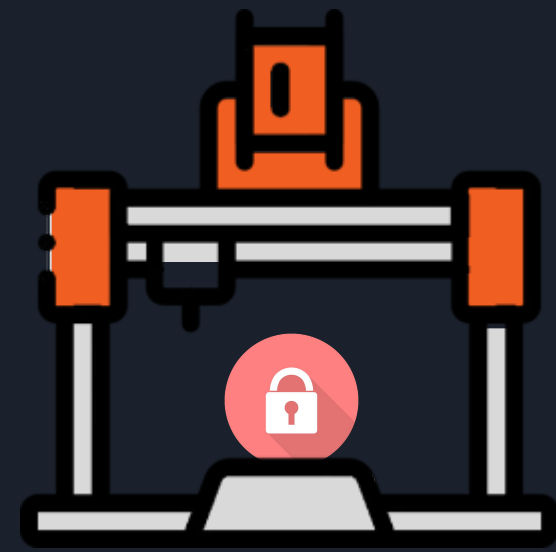


Figure 6. DBSCAN for 4320 files

## Conclusion

Interdisciplinary undergraduate researchers were able to demonstrate methods of detecting faulty files through statistical analysis and machine learning such that it can be further developed and implemented as a method of cyber security for companies.

The methods used were able to correctly identify defects for small datasets but experienced difficulty scaling up to larger datasets with broader defect types.





## Acknowledgments & Resources

Thank you to NYU Tandon as well as The National Science Foundation and the International Research Experience for Students (IRES) program for sponsoring this research and the students from outside of the USA to attend. The authors thank the professors and doctoral students who aided this research in providing information and resources for us to learn with.

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