Optimization of 3D printed objects

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Introduction

In traditional manufacturing, complexity is expensive. The cost of complexity takes the form of work-in-progress, tooling, and time to prototype. These costs can be hard to estimate because they depend on many factors. (Gorguluarslan et al. 2017) In contrast, in three dimentional printing, complexity is free. There is a clear trade off between the strength of an object and the amount of material used to print the object. In this project, we aim to show a method for simultaneously optimizing a 3D printable object for both strength and cost. three-dimensional printing is ready to become a viable alternative to conventional manufacturing. (Chen and Gabriel 2016)

Blender is an open-sourced design tool that can output .STL files. STL files specify the surface of a three-dimensional object in terms of triangles on the surface of the object. In the first phase, the lattice structure is generated using the mesh information of the structure geometry. (Gorguluarslan et al. 2017) A consequence of triangular faces is that they require significantly less computational time because neither projection of the polyhedron faces onto the appropriate coordinate planes nor reduction using Green's Theorem are necessary. (Eberly 2002)

Slic3r is an open-sourced tool to convert a model into printing instructions. It creates horizontal slices (layers) and generates tool-paths needed to fill them. It can also calculate the amount of filament to be extruded.

The goal of this project is to create an end-to-end flow from STL file to optimal G-Code file. In order to do that we have to design an experiment, slicing the STL file in many different ways. Focusing the infill parameters, we collect the metadata from the g-code output and enrich with some previously collected tensile strength data. Then we can model both the strength of the object and the amount of filament used to print the object. With those models in hand, we define a cost function that is proportional to filament used minus strength. Using a differential evolution algorithm to find the minimum cost.

Workflow

In Gorguluarslan et al. (2017), we present Falcon, a new system that follows a visual analytics approach to improve knowledge discovery in long and complex time series data with practical applications to the field of additive manufacturing.(Gorguluarslan et al. 2017) The calculated activation energy of nickel particle diffusion is 6.10 kJ/mole in the particle core, and 6.24 kJ/mole on the particle surface, which are reasonably in agreement with experimental data 7.89 kJ/mole. (J. Zhang et al. 2018)

In order to study the behavior of these technology fronts, and considering the data features of transversal developments, we opted for a subsetting strategy based on the gamma values returned by the topic modeling solution for each patent, so we could build sub-data sets containing the patents in which claims were clearly focused on the topics identified by our approach.(Garechana et al. 2019) During additive manufacturing processes, a huge amount of real-time big data is generated. (Majeed, Lv, and Peng 2018)

```
; generated by Slic3r 1.2.9 on 2019-04-15 at 19:51:45

; external perimeters extrusion width = 0.60mm
; perimeters extrusion width = 0.63mm
; infill extrusion width = 0.63mm
; solid infill extrusion width = 0.63mm
; top infill extrusion width = 0.63mm

M107
M104 S200 ; set temperature
G28 ; home all axes
```

```
G1 Z5 F5000 ; lift nozzle

M109 S200 ; wait for temperature to be reached
G21 ; set units to millimeters
G90 ; use absolute coordinates
M82 ; use absolute distances for extrusion
G92 E0
G1 Z0.350 F7800.000
G1 E-2.00000 F2400.00000
G92 E0
G1 X66.925 Y67.762 F7800.000
G1 E2.00000 F2400.00000
G1 X68.677 Y66.283 E2.07096 F1800.000
G1 X70.830 Y65.490 E2.14192
G1 X72.009 Y65.384 E2.17858
G1 X127.991 Y65.384 E3.91071
G1 X130.250 Y65.781 E3.98168
G1 X132.238 Y66.925 E4.05264 F1800.000
G1 X133.717 Y68.677 E4.12360
G1 X134.510 Y70.830 E4.19456
G1 X134.616 Y72.009 E4.23121
```

Figure **??** shows an example of the contents of a gcode file.

Falcon provides linked visualizations from both temporal and statistical orientations with automated analytics to highlight interesting features. From our informal evaluations of the applied use of Falcon in additive manufacturing, we have learned that non-visualization experts can be vital members of interdisciplinary design teams as they help design new capabilities that respond to their actual needs, and they quickly employ new visual analytics techniques in creative ways to solve problems.(Gorguluarslan et al. 2017) The parallels between the analytical goals in additive manufacturing and other domains suggest that these capabilities are broadly applicable to many domains as they help users develop and refine a more complete mental model of complicated and large-scale time series data. (Steed et al. 2017) These matrices were analyzed using a topic modeling technique, which has shed light on the technology fronts being developed under the broad field of three-dimensional printing. (Garechana et al. 2019) Metrics built on patent data were used to characterize the rate of change of technology fronts, analyzing each of these on a relative basis with respect to the values produced by the rest of the fronts. (Garechana et al. 2019) Majeed, Lv, and Peng (2018) provides a good basis for the application of big data analytics in the additive manufacturing process. (Majeed, Lv, and Peng 2018) Majeed, Lv, and Peng (2018) brings three contributions to successfully implement the big data analytics in the area of additive manufacturing. (Majeed, Lv, and Peng 2018) The first contribution is the architecture of big data-based analytics and its key components in additive manufacturing. (Majeed, Lv, and Peng 2018)

Simulation and Modeling

Figure 1 shows our workflow.

In this project, we used FlashForge 3D printer to obtain a large cube as a STL file and pass it through a Slic3r to format it as a G-Code. We then model tensile strength from a csv file obtain from Kaggle Dataset. After applying that model to our metadata, we model filament usage as a function of similar inputs.

When we modeled strength, we found that the most important parameter was wall thickness. Extrusion temperature, and fill density were also significantly predictive of tensile strength. Every other parameter we looked at was discarded, the top ten features are summarized here.

We used a random Forest to predict tensile strength from these four parameters.

Predictors of tensile strength

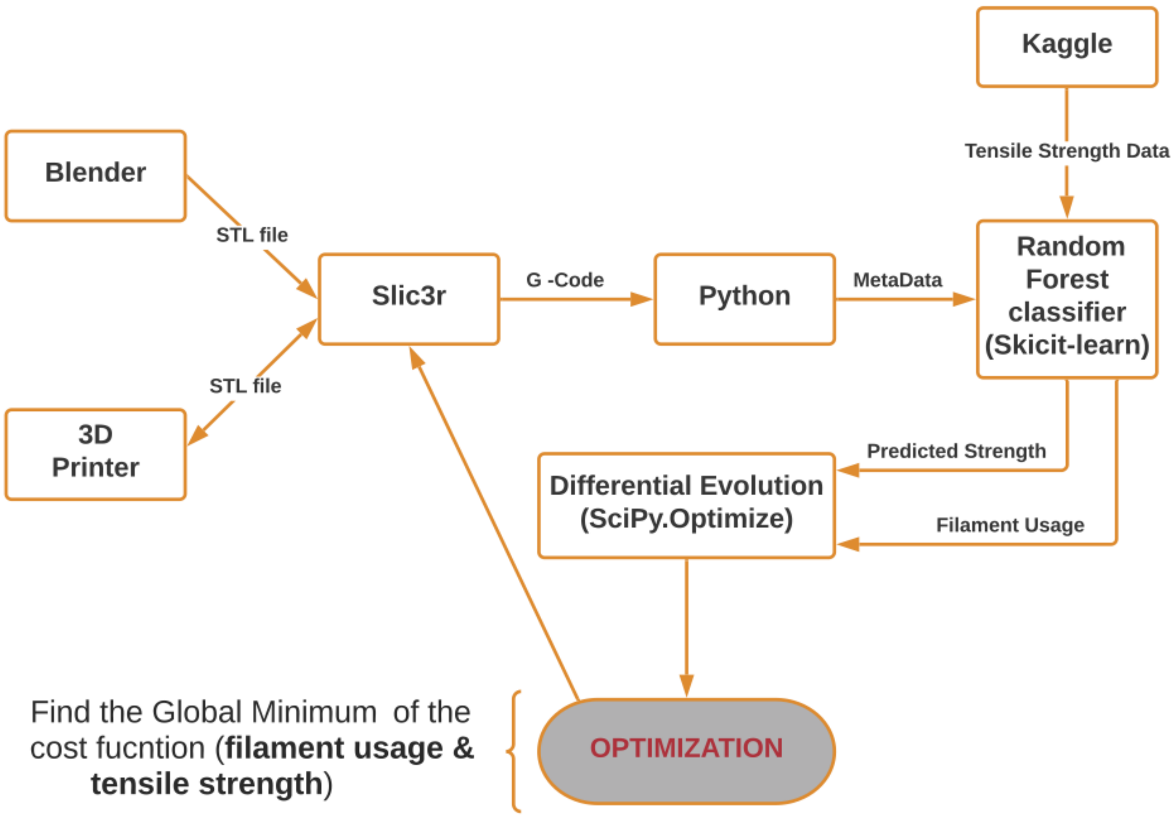

Figure 1: workflow diagram

column	description	units
wall thickness	Number of solid layers on surface	# of layers
nozzle temperature	Extrusion temperature	°C
infill density	percent of volume to fill with pattern	%
layer height	height of each layer	mm
fan speed	speed of cooling fan	% of max
bed temperature	temperature of platform	°C
print speed	speed of robot arm	mm/s
infill pattern	pattern of non-solid layers	Rectilinear or Honeycomb
material	material	ABS or PLA

```
for configuration in list(it.product(*configurations.values())):
    metarow = pd.Series(configuration,index=configurations.keys())
    output_file_format="[input_filename_base]"
    print("{} out of {}".format(count+1,total))
    cmd=["slic3r"]

    for key,value in zip(configurations.keys(),configuration):
        #print("adding {} with value of {} to cmd".format(key,value))
        metarow[key]=value
        if value:
            cmd.append(str(key))
            if not isinstance(value,bool):
                cmd.append(str(value))
        output_file_format+="_"+flag2placeholder(key)

    cmd.append("--output-filename-format")
    cmd.append("{count}_{output_file_format}_.gcode".format(count=count,
                                                          output_file_format=output_file_format
                                                         )
              )
    cmd.append(input_file)
    metarow = metarow.append(pd.Series(count,index=["filenumber"]))
    cmd_str=''
    for arg in cmd:
        cmd_str += ' '+str(arg)
    print(cmd_str)
    try:
        check_output(cmd)
```

Figure 2 shows our the relative importance of the top 10 feature for predicting tensile strength.

Figure 3 shows predicted tensile strength plotted against actual tensile strength

Predictors of Filament usage

column	description	units
infill every layers	Infill every N layers	#
fill density	volume to fill with pattern	%
layer height	height of each layer	mm
infill extrusion width	filament flow width	mm
fill pattern	fill pattern	fill pattern
perimeters	horizontal solid layers	perimeters
fill angle	horizontal infill pattern	degrees

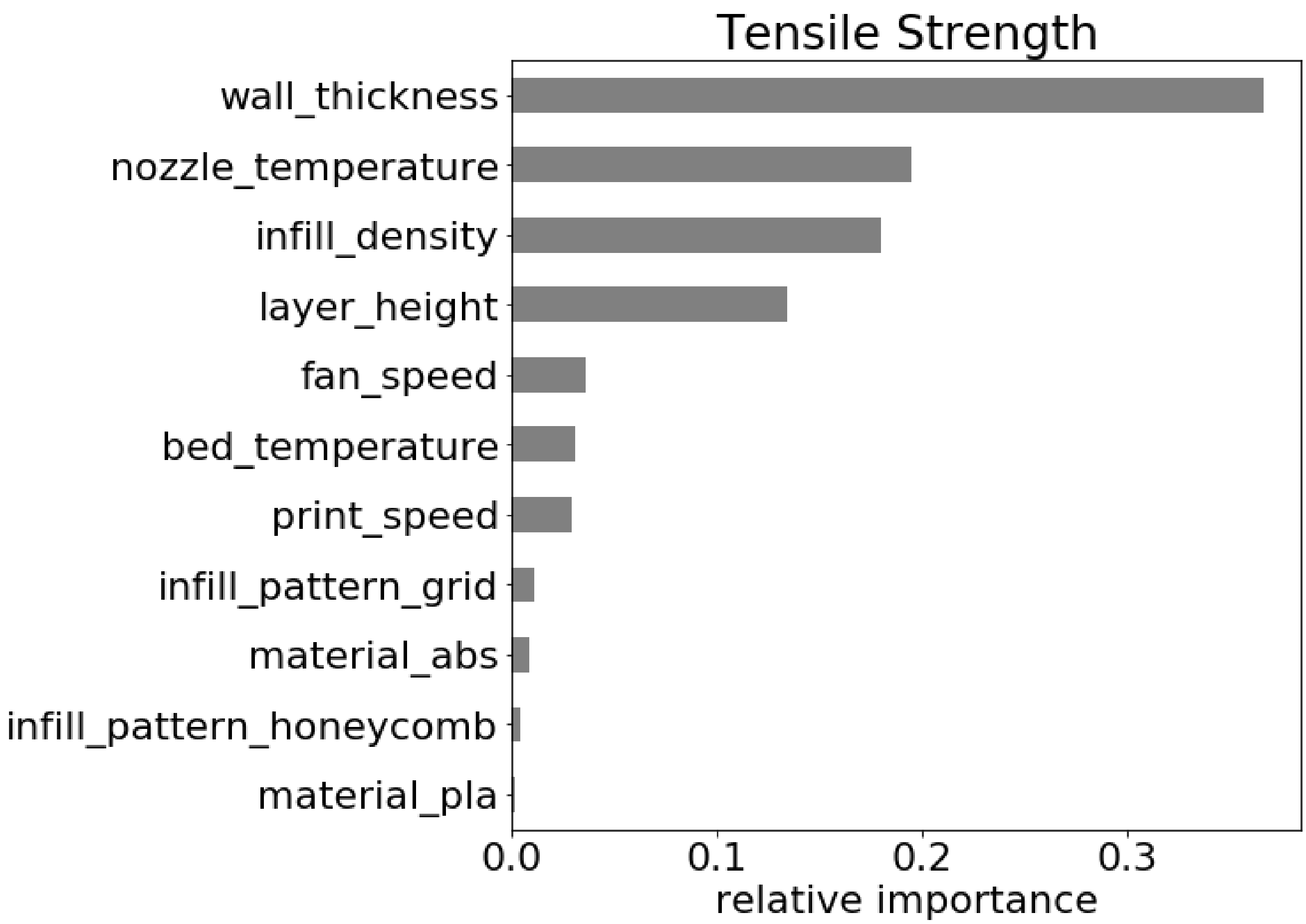

Figure 2: relative importance for tensile strength

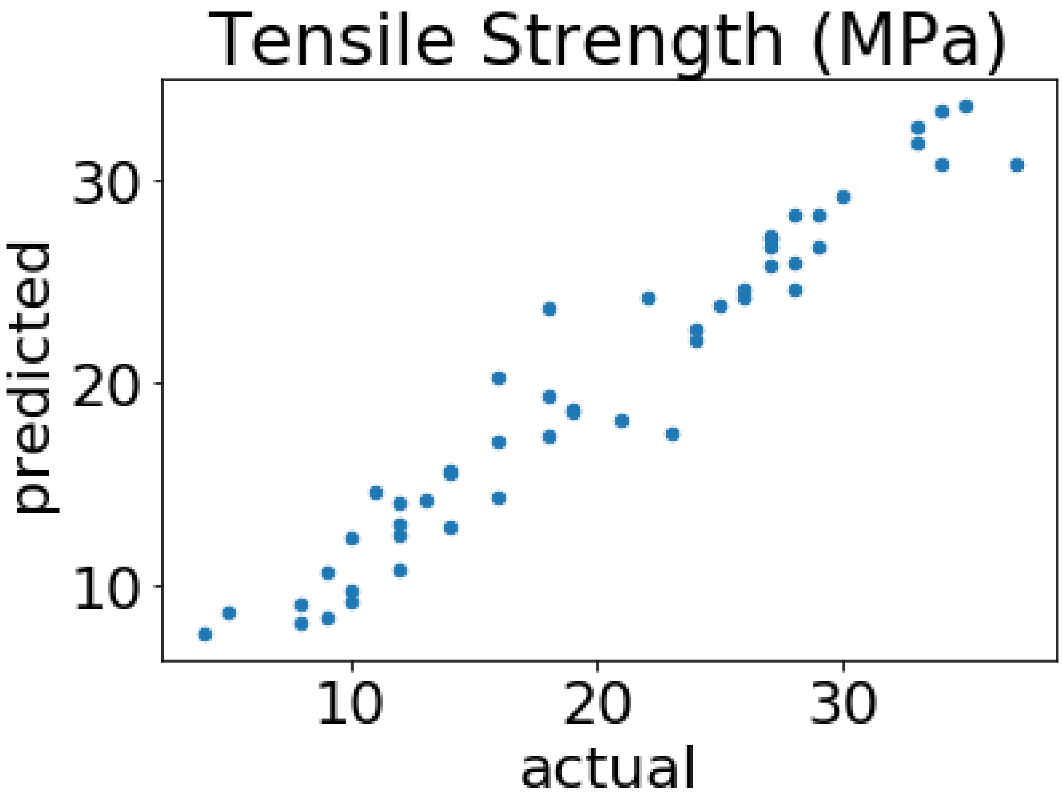

Figure 3: predicted tensile strength vs actual tensile strength

Figure 4 shows our the relative importance of the top 10 feature for predicting filament usage.

Figure 5 shows predicted tensile strength plotted against actual tensile strength

For filming usage, we found that the number of skipped layers, in-fill density and layer height are significantly important. Every other future was discarded. We used a 2nd random Forest to predict filament usage from these three parameters.

Improving the accuracy these models is beyond the scope of this project.

Looking at a plot of strength vs filament usage we see an opportunity for optimization in the top left corner where using less filament results in reasonably strong object.

Chen and Gabriel (2016) found thickness of Fill, Fill Rate, Extruder Speed and Extruder Head Temperature have an effect on tensile strength.(Chen and Gabriel 2016)

Model Limitations

The limitation of Majeed, Lv, and Peng (2018) is that only a framework is proposed, and the algorithm for data analysis, such as association, classification and clustering are not studied in Majeed, Lv, and Peng (2018). (Majeed, Lv, and Peng 2018)

To do so, an initial manufacturable lattice structure is generated under the overhanging areas. (Gorguluarslan et al. 2017)

failure	effect	coutermeasure
overhang	collapse	add support structures
shinkage	deformation at corners	increase fan speed

failure	effect	coutermeasure
pillowing	sagging infill	increase fill density
stringing	unintended structure	decrease retraction speed

Over-hanging areas with no common support structures (two disjoint subgraphs) could be separated in various clusters, and each cluster could be optimized again with a normal optimization. (Gorguluarslan et al. 2017)

While support structures are outside the scope of this project, Gorguluarslan et al. (2017) provides a framework to optimize support structures for additive manufacturing.

Optimization

In order to find a minimum cost we can ask a genetic algorithm to modulate these five parameters and search the space. Here we've shown how fill density collapses towards an Optimum just under 50% fill density.

Looking at a default slicing rectilinear infill pattern and a single wall infill density about 13%, we compared it to our Optimum slicing infill about 50% pattern is Honeycomb and four layers but they use about the same amount of material in order to generate better initial populations. (Gorguluarslan et al. 2017)

The analysis of the results concludes that the process capability indices (Cp and Cpk), can be improved and at the same time optimal parameters can be identified using Six Sigma DMAIC (Define, Measure, Analyze, Improve, and Control) approach which is a win-win situation. (Chen and Gabriel 2016)

A BESO(Bidirectional Evolutionary Structural Optimization)-based optimization process is used to find the optimum struts' thickness distribution. (Tang et al. 2017)

The heterogeneous lattice structure optimized by the proposed method has a better performance compared to the homogenous lattice structure. (Tang et al. 2017) Finally, the process can be optimized to obtain a larger feasible area for design and optimization. (Tang et al. 2017)

Relations between strut dimensions and mechanical properties can provide a feedback to lattice simulation and optimization model with more accurate material properties. (Tang et al. 2017)

In order to further improve the optimization of the support structures, the objective function (that only includes the material volume) could be extended, by taking into account the support removal and finishing costs.(Gorguluarslan et al. 2017)

The first example, i.e. the cantilever beam example, is used to show that the proposed framework can produce an optimized structure with minimal computational cost by considering the minimum manufacturing limit. (Gorguluarslan et al. 2017)

The second example is used to investigate the minimum diameter value that can be fabricated using the SLS process that will be used for the fabrication of the optimized lattice-based pillar structure. (Gorguluarslan et al. 2017)

The third example was a real-world application of the lattice structure optimization for a seat-bottom frame with a larger number of design variables when compared to the previous examples. (Gorguluarslan et al. 2017)

Moreover, it is shown in the second and third examples that the two-phase optimization framework can successfully find an optimized structure that can be fabricated once the minimum value is known for the specific additive manufacturing machine. (Gorguluarslan et al. 2017)

Gorguluarslan et al. (2017) has shown that using a genetic algorithm performs better traditional generation strategies.

It is also shown that the optimized structure has better performance compared to alternative existing methods. (Gorguluarslan et al. 2017)

Figure 6 shows tensile strength plotted against filament usage. add more texere

Figure 7 shows how the progress of the optimization algortihm as it converges on the optimal fill density.

Figure 8 shows a cross sectional view of default slicing settings.

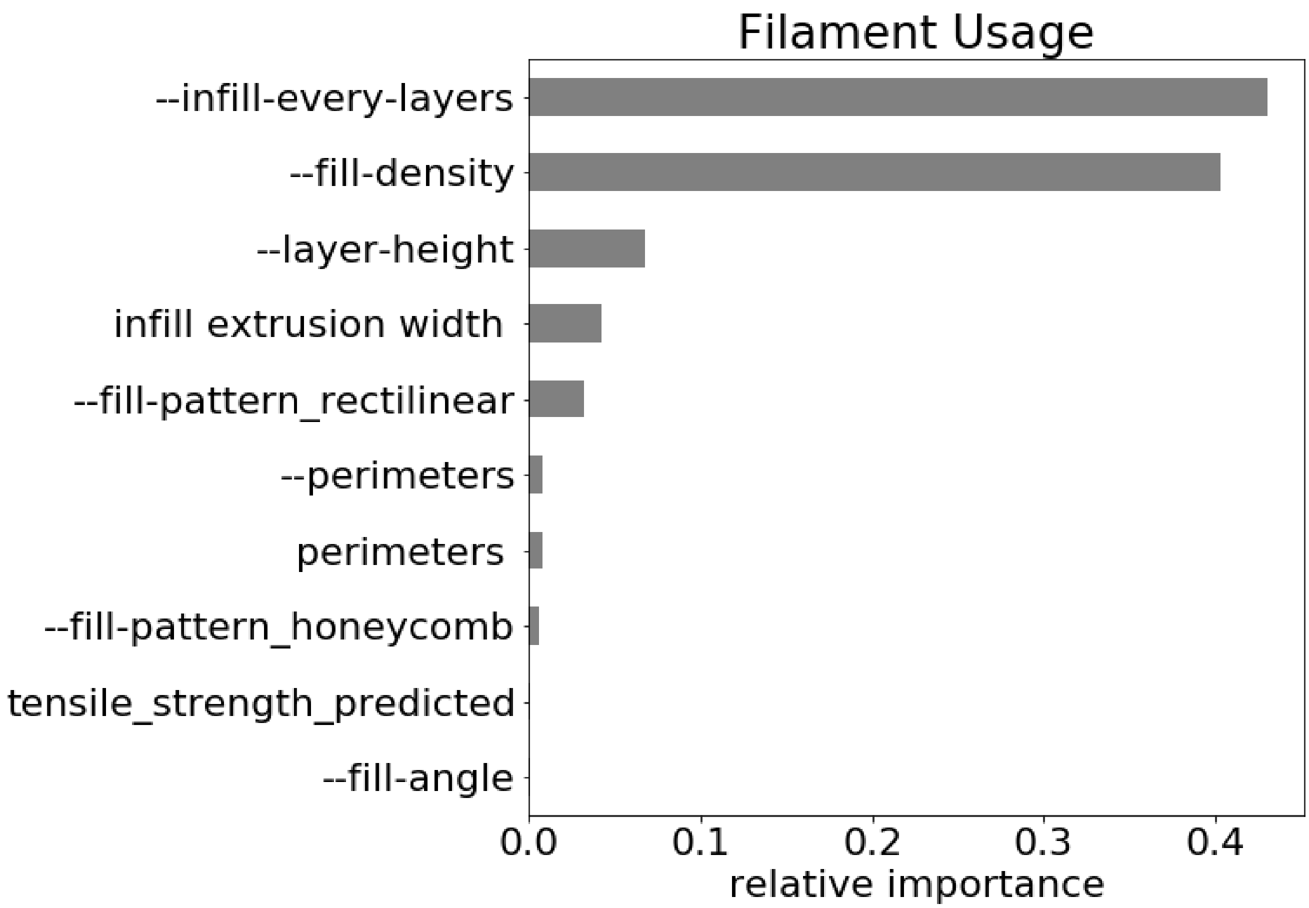

Figure 4: relative importance for predicting filament usage

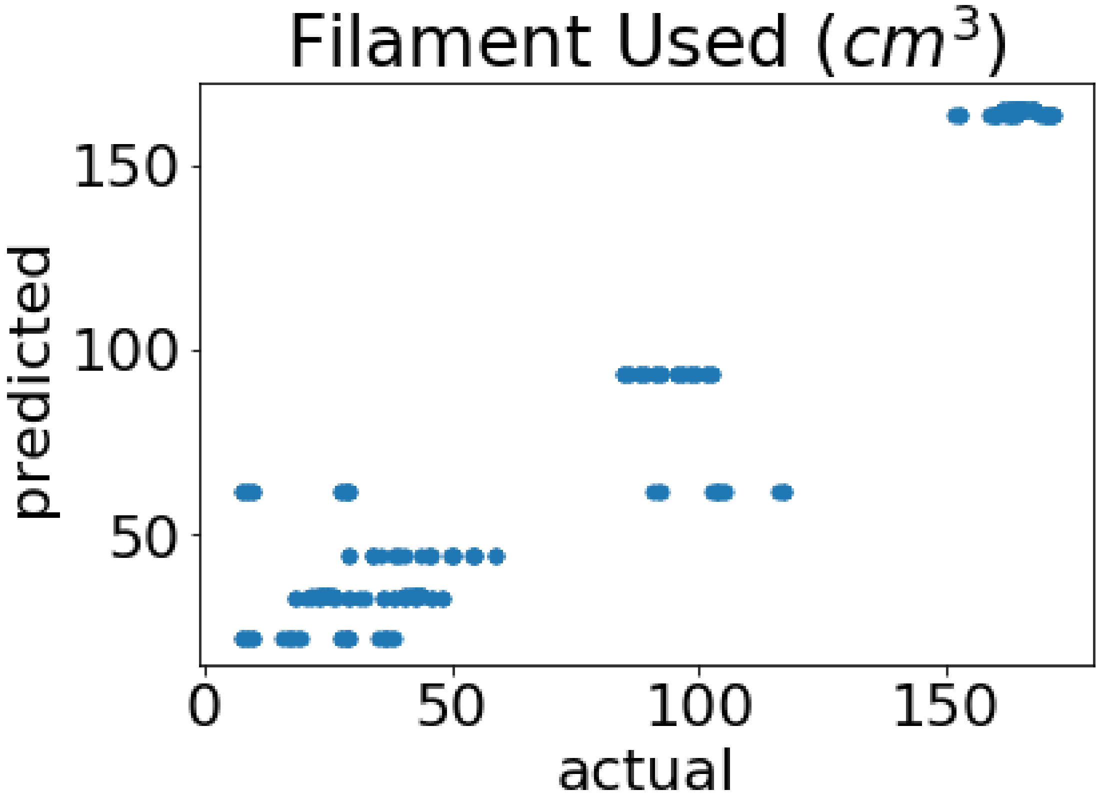

Figure 5: predicted filament used vs actual filament used

Figure 9 shows a cross sectional view of our optimal slicing settings.

Summary

This paper discusses a machine learning method namely Random Forest to evaluate the cost function of filament used to print objects. The Random Forest not only resulted in lower cost but also shows linearity pattern in the amount of filament used. For filament usage, we found that the number of skipped layers, infill density and layer height are significantly important.

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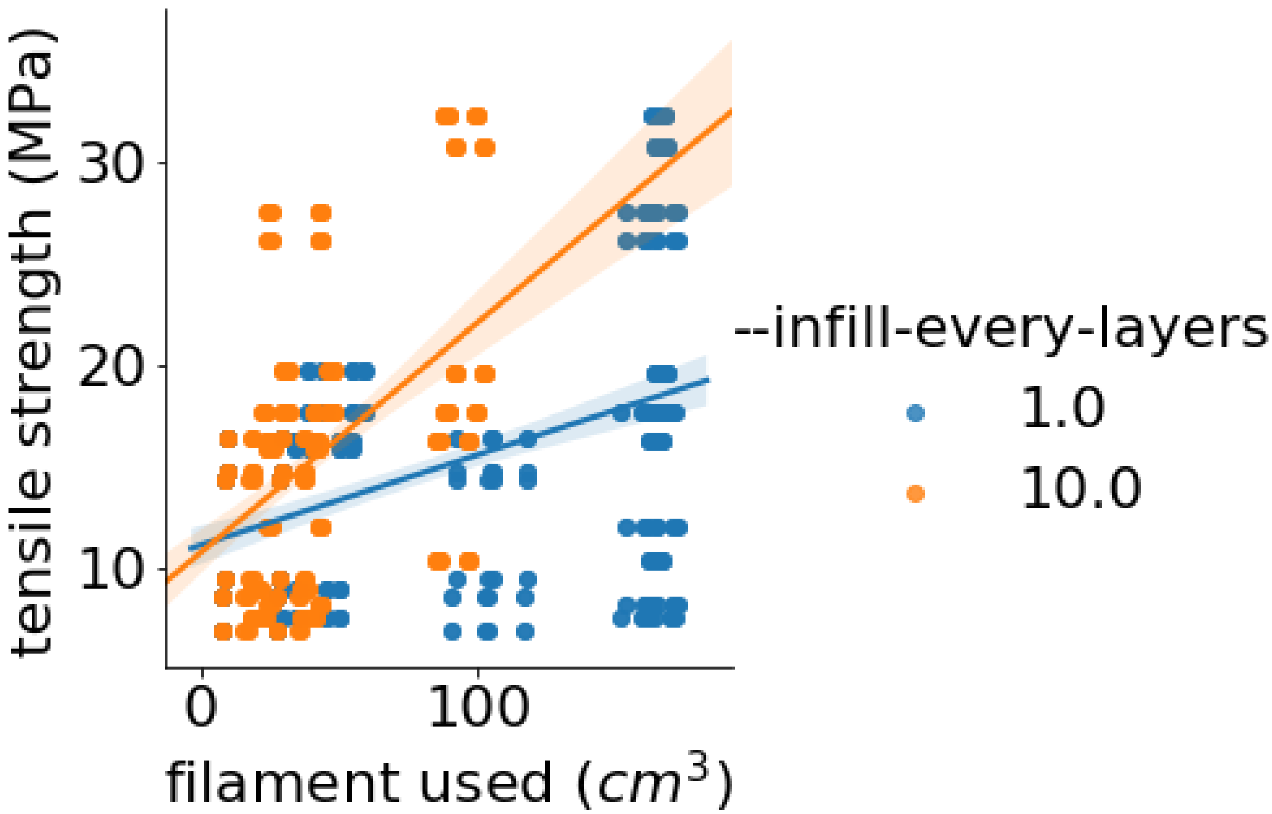

Figure 6: predicted filament used vs actual filament used

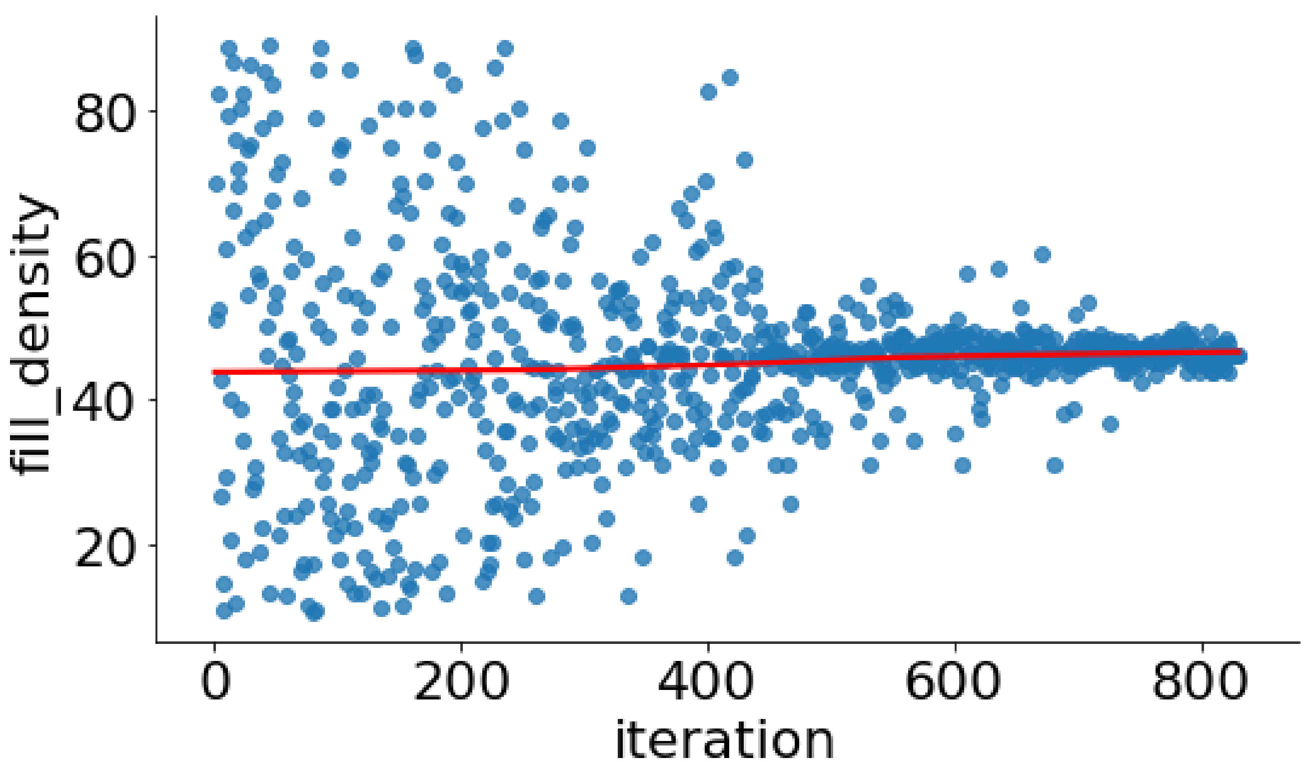

Figure 7: predicted filament used vs actual filament used

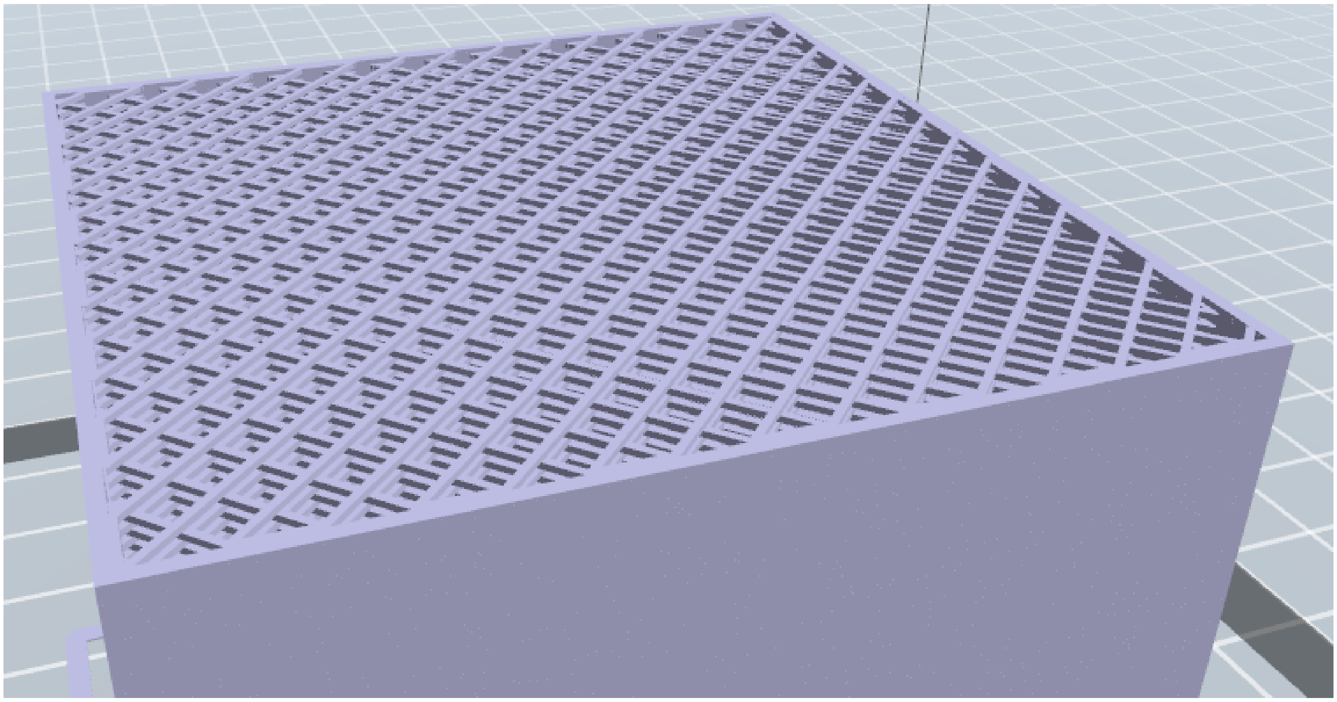

Figure 8: predicted filament used vs actual filament used

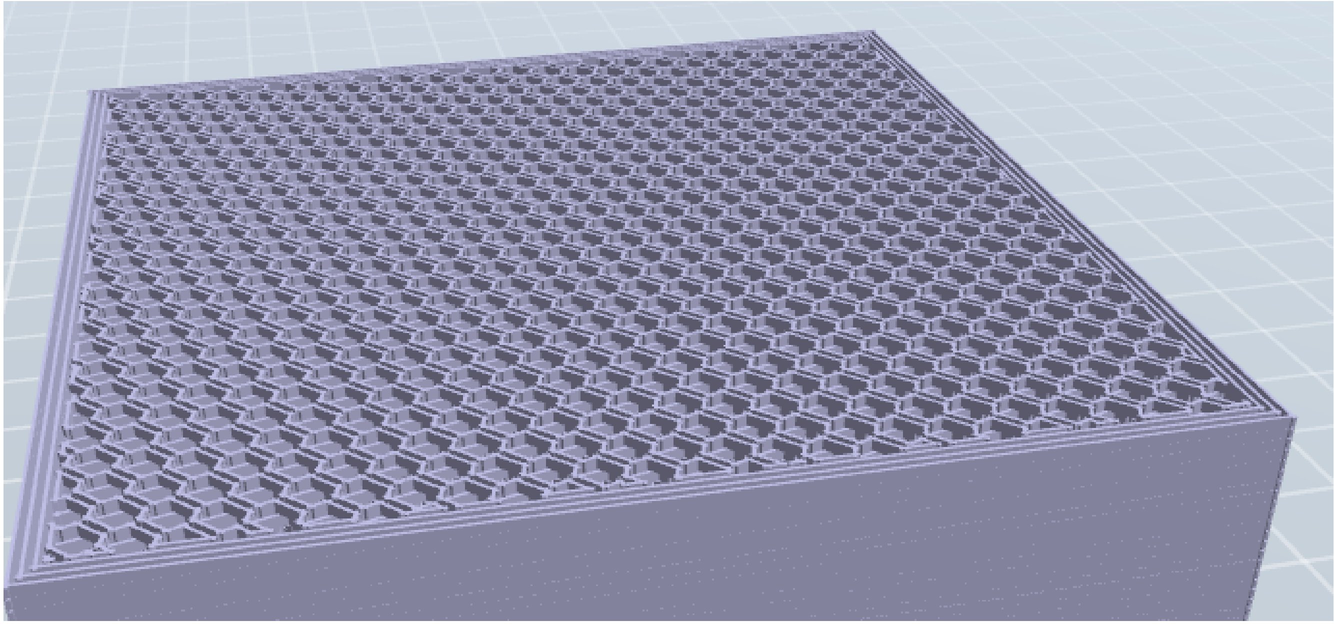

Figure 9: predicted filament used vs actual filament used

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