The Effect of Layer Height and Filament on the Quality and Mass of 3D Printed Objects

Deva O'Neil, Bridgewater College

4/23/2022

I. INTRODUCTION AND BACKGROUND

A long-term goal of the BC Physics department is to introduce more students to additive fabrication (3D printing) in the context of project-based learning. Research studies of physics labs show benefit from allowing students agency in decision-making and the opportunity to fix mistakes and iteratively improve experimentation [1]. Incorporating 3D printing into physics labs has the potential to achieve similar benefits of project-based learning and student-driven design [2][3]. The BC physics department has two Jellybox printers and two Qidi printers. The Qidi printers are easy to use and are dedicated for use in the physics classroom/lab. The Jellyboxes require more fiddling to calibrate, and tend to be less reliable due to not having a heated bed; they were purchased with Physics Club funds, and we reserve those for hobby projects under the direction of Physics Club.

When designing and producing an object, one first creates the design in a CAD program. To convert the object into a plan for printing, which is done layer by layer, slicing software is used to set parameters such as the size of each layer (layer height), the speed of printing, and the type of filament (material). The Qidi printers and the Jellyboxes are made by different companies; each has their own slicing program, and thus will produce their own process for printing.

Various aspects of the printing process have been found to have an effect on print quality. For example, in designing an object, the orientation of the object relative to the build plate affects both the need for supports (to support 'overhanging' mass during the print process) and the quality of the final object [4] (since a layering effect gives a rough edge to vertical sides). In the process of converting the design to a .gcode file for the printer (called "slicing"), other parameters can be set, such as infill percentage (how much of the interior is filled with filament) and the layer height.

II. PURPOSE

The purpose of this project is to pilot a potential class project for a physics or data science class. The project should allow students to design their own object, and create data that is appropriate for a regression analysis and/or ANOVA. Using scales available for lab, students have the ability to measure the mass of a printed object with a precision to the nearest 0.01 gram. Hence, the unit of data for this project will be the mass of the object in grams. With sufficiently small objects, the printers can print batches of multiple objects at once. The fundamental research question of this project is what variables predict the quality (smoothness, uniformity) and mass of the print. As a proxy for uniformity, the standard deviation of a set of objects (one "batch") will be studied. Hence, the possible outcomes are the mass of an object and the standard deviation of the mass of a batch.

To study the effect of various parameters on the output, I asked two of my students (Hannah McPherson and Salim Solayman) to design a small object in AutoCAD. To maximize the challenge of producing a smooth build, I requested an object with holes and sharp corners. They delivered the design of a "twisty" cube with a pyramidal point on top.

In this project, I chose to minimize the need for overhangs by orienting my object pointed end upward, and thus did not vary the orientation. I also used only the Qidi printers. I did test a set of masses with the Jellybox printers, and found that it was difficult to vary the layer height, or any other parameter, and still have intact objects printed. The Jellyboxes seem to work only with optimized parameters. The Qidis, however, have a number of independent variables that can be adjusted. For this project, I chose the following independent variables:

1. The layer height, measured in mm.
2. The filament (binary) – red or green.

In principle, all PLA filament of a given width should produce the same builds. However, one of my spools (red) was suspected to have quality control failure; it arrived with broken/burned pieces instead of being in one intact spool. This study compares it to a normal spool (green) to determine if it is defective.

In the future, other parameters of interest could include the infill percentage (in this study, all batches used 20%), the type of filament (PLA vs. ABS) and the print speed.

In total, 159 objects were printed (18 batches).

III. HYPOTHESES

The Qidi slicer software offers various 'resolutions' for each build. The default options are 'Quick, Fine, High, Extra Fine,' corresponding to layer heights of 0.2 mm (on quick speed), and 0.2 mm, 0.16 mm, and 0.12 mm (on normal speed). Keeping the speed at the normal level, I varied the layer heights from 0.1 mm to 0.5 mm, covering a greater range than what the printer is optimized for. My hypothesis is that there should be a lowering of quality if the layer height is too small or too large. Large layer heights create a "step" effect, which makes the edges rough and impede the ability of the printer to achieve the sharp edges and hollow tubes of the design. Layers that are too small require many extra passes of the printer, and may exceed the ability of the hot-end to finely extrude the correct width of filament. Thus, I hypothesize a non-linear dependence of the standard deviation on the layer height, possibly a concave-up parabola. This behavior would be consistent with the results of Vaezi et al., who found that an increase in layer height from 0.087 to 0.1 mm produced better 'uniformity' [5]. However, research on wood fiber PLA has found that smoothness (measured with a stylus profilometer) increases across a range of 0.05 mm to 0.3 mm [6]. The actual point at which the layer height becomes too small may vary with the type of filament and the model of printer. In the Qidi slicing software, the characterization of the smallest layer height as 'Extra Fine' may thus be misleading, as smaller layer height does not necessarily lead to a smoother product. This project will help us determine what layer height maximizes the quality / smoothness of the build.

What one should expect as far as the mass of an object is not as clear. Since the infill percentage is less than 100%, it may be that a coarser layering would produce thicker bottoms/tops, increasing the mass of the object. If so, there could be an increase in mass as layer height increases. However, most of the interior would remain infill, so I wouldn't expect a strong effect. Figure 1 below illustrates the possible influence of layer height on the total mass.

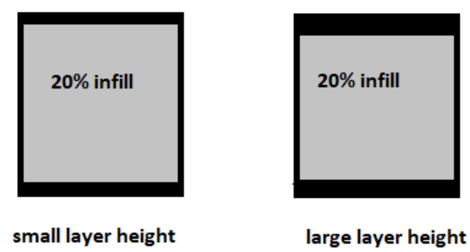


Fig. 1: The possible influence of layer height on mass.

I would not predict much effect of filament color on the mass. Even if the red filament is defective, it may still have the same density as the green filament. We will still use this as a null hypothesis and see if there is an effect.

	Null Hypothesis	Alternative Hypothesis
Filament	The red filament is not defective (standard deviation is not higher than for green). The masses of the objects do not depend on which filament is used.	(1) The standard deviation of the mass of each batch is higher for the red filament. (2) The mass changes based on the choice of filament.
Layer Height	No effect of layer height on the mass or standard deviation of the mass	(1) Layer height has an optimal value that minimizes the standard deviation (maximizes the quality) (2) Layer height is a predictor for the mass of the object

IV. DATA

An ideal data set would have a large sample size (determined in advance by a power analysis to prevent underpowered studies), normally distributed data, no missing data, and be formatted in 'tidy' style with a single column representing each observation. The empirical measure of the outcome should be a good measure of the independent variable. Methodologically, an ideal research study should avoid omitted variable bias and implement a pre-determined protocol for variable selection, data collection procedure, control of confounding factors, and number of batches (preferably registered in advance with a journal to avoid publication bias). My data aligns with some of these objectives but not others, as described below.

- Format

I recorded the data in 'tidy' format and coded it by filament type, layer height, trial (batch number), and whether the print failed:

```
library(rstatix)
library(tidyverse)
widg<- read_csv("tidyTwistyBoxData.csv")
# Use the full data set for inspecting, then group by trial for analysis
df <- widg %>% mutate(layer_height=as.factor(layer_height), trial=as.factor(t
rial))
p<- df %>% ggplot(aes(x=layer_height,y=mass,color=trial))+geom_boxplot()
p + geom_dotplot(binaxis='y', stackdir='center', dotsize=.4)
```

Each batch contained 8 – 10 printed objects, all with the same layer height and filament type. Because I took the data myself, I was able to avoid missing data. The resulting data is shown in Figure 2. Each object is represented by a dot, color-coded by batch.

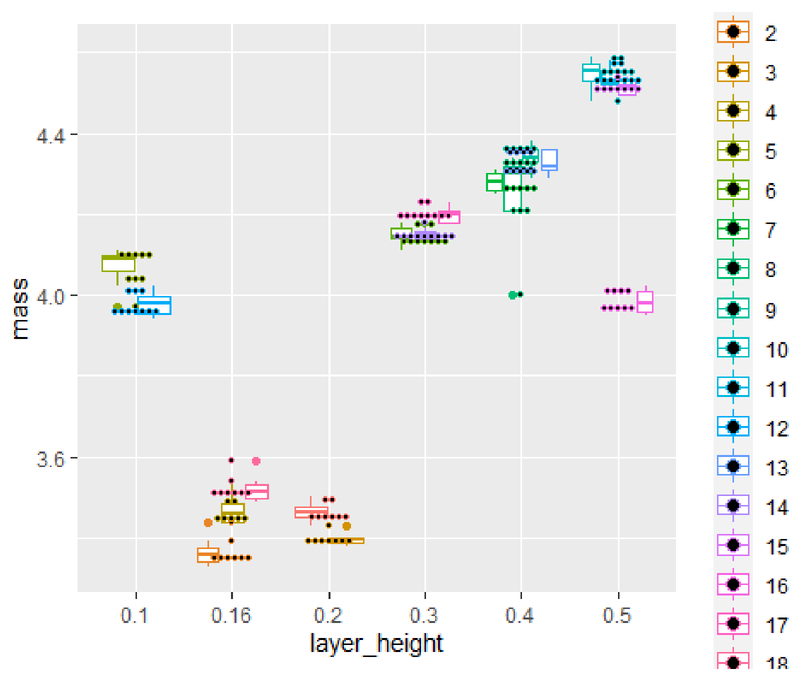


Fig. 2: The distribution of masses with layer height.

- Control of confounding factors and omitted variable bias

Ideally, the only variables should be the filament type and the layer height. Originally, I thought that using two printers, both Qidis, would not introduce the potential for a confounding variable, since they both ran the same gcode. However, at batch #8, one of the printers produced a defective set of objects, with layers clearly missing (see Figure 3).

Fig. 3: A failed print, probably due to bad alignment / leveling.

These failures can happen when the bed gets out of alignment with the extruder (in this case, it appears that the extruder may have been too far from the bed). Re-leveling the bed fixed this problem. This batch was flagged ‘defective = 1’ in the data file. A similar problem occurred on the other printer in batch 16. I made the mistake of adjusting the leveling before batch #16 to try to keep the prints from sticking to the bed. This corrupted the alignment (as indicated by a very poor quality batch, with dented tops and lumpy layers – see the 2 objects on the left in Figure 4). My TA Hannah McPherson re-leveled it for me. This could have resulted from too little space between the extruder and the bed, or an uneven bed.

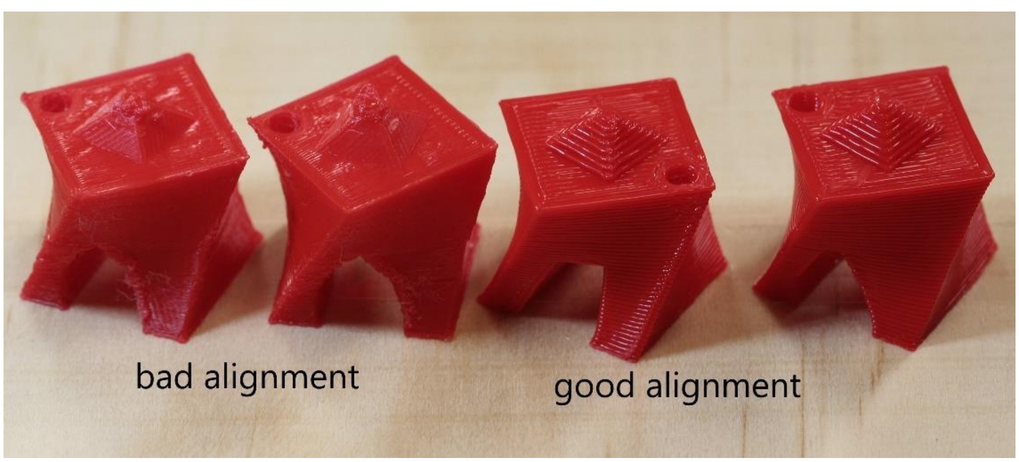


Figure 4: Bad alignment causes another batch to fail.

Unfortunately, there is no way to guarantee that the alignment before the adjustment is exactly the same as the alignment after it was fixed again. I tagged batch #16 as defective, but batches 17 and 18 may be suspect, since they were printed after the machine was tinkered with. This methodological error could introduce a confounding factor into the data, since batches printed after #16 could have been printed with better alignment, or worse alignment, than previous ones.

- Normality

The mass data for each trial does appear normally distributed in each category of layer height, with the exception of 0.1 mm and 0.5 mm. In the latter case, this problem will resolve when one excludes from analysis batch #16. In the case of the 0.1 mm batches, their histogram (Figure 5) is somewhat bimodal instead of normal, due to the 2 batches having more variation between the groups than within each group. The problematic nature of printing with a layer height of 0.1 mm will be discussed at length later in this paper. For now, we will say that normality holds overall, but we will need to remove the failed batches.

```
#histogram (each layer height has a different color)
df %>% ggplot(aes(mass,color=layer_height))+geom_histogram(binwidth = 0.02)
```

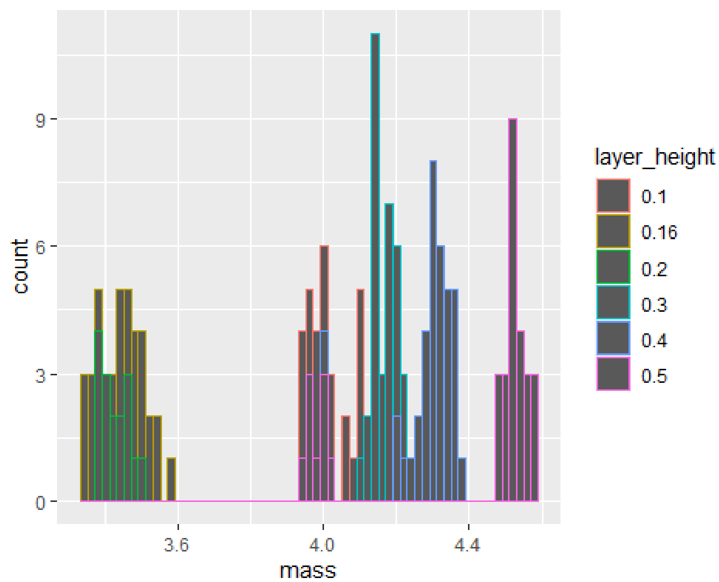


Fig. 5: Inspecting the normality of the data for each value of layer height.

The QQ plot (Figure 6) for each layer height is roughly linear, with the exception of 0.1 mm, reflecting its more bimodal distribution.

```
# QQ Plot - shows each layer height in a different color
qplot(sample = mass, data = goodwidg, color=layer_height)
```

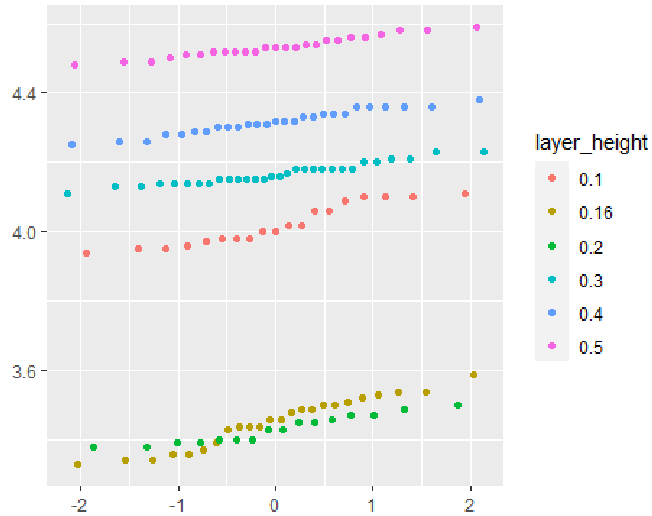


Fig 6: QQ Plot, color-coded by layer height.

```
q<- goodwidg %>% ggplot(aes(x=layer_height,y=mass,color=trial))+geom_b
oxplot()
q<- q + geom_dotplot(binaxis='y', stackdir='center', dotsize=.4)
q
```

Figure 7 shows the final distribution of data, with failed prints removed from the data set:

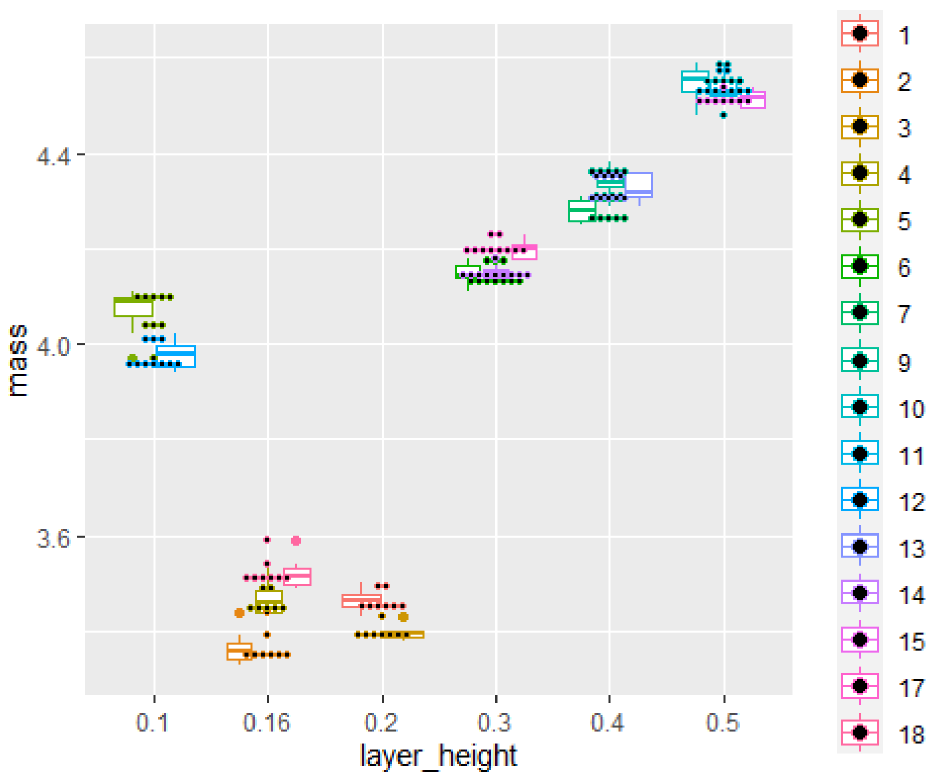


Fig. 7: Data set with failed batches removed.

A Shapiro test was run on each layer height individually to test for normality. The two failed batches (#8 and #16) were first included for completeness, although they will be excluded from analysis for reasons already explained. The 2nd test excludes the failures and confirms the normality assumption for all layer heights except for 0.1 mm.

```
# Shapiro Test: Null hypothesis means data is normal
# This test includes all batches, including defective ones
widg  %>% group_by(layer_height)%>%  shapiro_test(mass)

## # A tibble: 6 x 4
##   layer_height variable statistic           p
##          <dbl> <chr>        <dbl>       <dbl>
## 1         0.1  mass         0.893 0.0371
## 2         0.16 mass         0.949 0.255
## 3         0.2  mass         0.917 0.149
## 4         0.3  mass         0.945 0.123
## 5         0.4  mass         0.750 0.00000189
## 6         0.5  mass         0.658 0.000000120

#remove defective prints and re-run tests
goodwidg<- df %>% filter(defective==0)
goodwidg%>% group_by(layer_height)%>%shapiro_test(mass)

## # A tibble: 6 x 4
##   layer_height variable statistic      p
##   <fct>        <chr>        <dbl>  <dbl>
## 1 0.1          mass         0.893 0.0371
## 2 0.16         mass         0.949 0.255
## 3 0.2          mass         0.917 0.149
## 4 0.3          mass         0.945 0.123
## 5 0.4          mass         0.967 0.513
## 6 0.5          mass         0.969 0.621
```

Overall, there is no evidence for non-normality for layer heights above 0.1 mm once the failed batches are excluded.

- Measurement of outcome

The measurements of mass are expected to provide a reliable direct measurement for the mass outcome. The masses were only measured once for each object, but in initial testing, it was found that repeated measurements of the mass of one object on the same scale change the mass reading by an amount less than 0.01 grams (which is the precision limit of the scale, and far below the standard deviation of each batch).

However, standard deviation is an imperfect proxy for quality. Extreme variations in output would certainly indicate poor quality prints, but minor issues of quality (eg, a lack of smoothness) may not show up as variation in the mass in the data sets. Hence, variation in standard deviation may underrepresent true variation in quality.

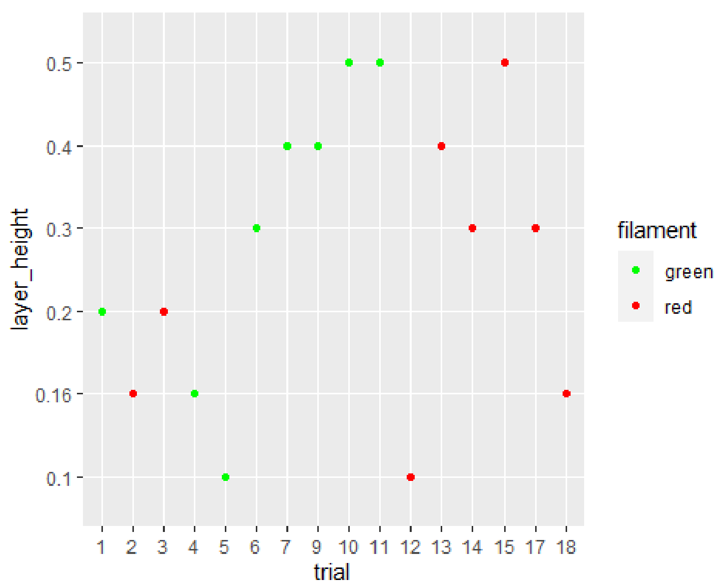
- Designing a data collection protocol in advance

It is ideal to alternate between green and red filament in each printer. It would be a bad idea to do all the red prints and then all the green prints, since there could be some kind of alignment drift over time that could make the filament appear that it was affecting the outcomes, when in reality it would be the effect of print order. However, it becomes apparent from the graph of trials (Figure 8) that the switching of the filaments was not as well shuffled as it could have been, and a protocol should have been created in advance that would ensure good shuffling. Similarly, a protocol for randomizing the variation of layer height as the experiment progressed would have been helpful.

```
#methodology check - is the shuffling random, or does it drift with time?
goodwidg %>% ggplot(aes(x=trial,y=layer_height,color=filament))+geom_point()+
scale_color_manual(values = c("green" = "green","red"="red"))

cor(df$trial,df$layer_height)

## [1] 0.3479296
```



#

Fig. 8: The order of variation of layer height and color.

Ideally, the correlation between trial number and layer height should be close to zero.

V. Modeling Strategies

Our GLM for the effect of layer height and filament on the two outcomes (mass and standard deviation) introduces a new variable, $layer\_height^2$, since we hypothesize that layer height has a medium value that optimizes quality.

Modeling Standard Deviation

Standard deviation was modeled using multiple formulas (linear and quadratic) to test the effect of the quadratic term. The input data is shown in Figure 9.

```
widgetData<-widg %>% filter(defective==0) %>% group_by(trial)%>%mutate(mu=mea
n(mass),std_dev = sqrt(var(mass)))

df <- widgetData %>% group_by(trial,filament,std_dev,layer_height,mu) %>% sum
marize()

df <- df %>% mutate(layer2 = layer_height^2)

df %>%  ggplot(aes(layer_height,std_dev,color=filament))+geom_point()+ scale_
color_manual(values = c("green" = "green","red"="red"))+ geom_smooth(method =
"lm",formula = y~x +I(x^2))

reg<- lm(std_dev ~layer2+layer_height + filament,data=df) #Std dev, quadratic
reg_sd<- lm(std_dev ~ layer_height + filament,data=df) #Std dev,  linear
```

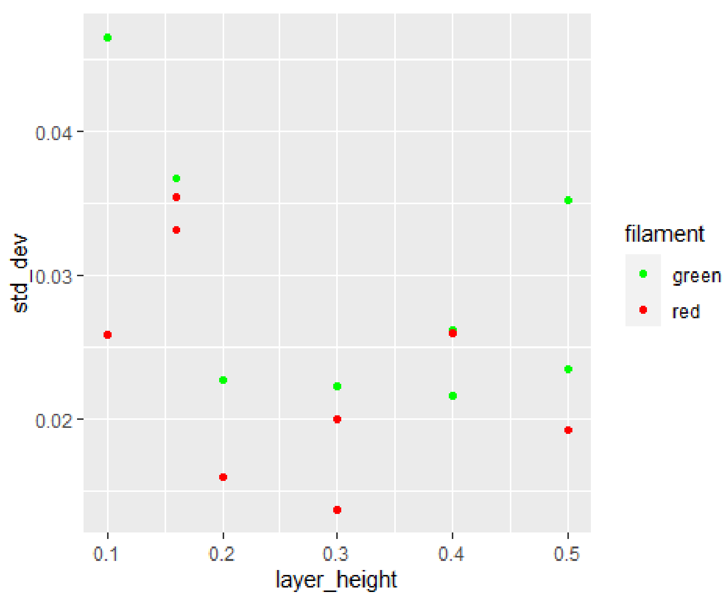


Fig. 9: The standard deviation of each batch.

Modeling Mass

It was not hypothesized that the mass values should also show a quadratic pattern. However, a look at the data (Fig. 10) suggests that there may be a minimum of mass just as there is a minimum of standard deviation. Three approaches to modeling the effect of layer height were attempted: Linear, quadratic, and categorical.

```r
#Effect of layer height on mass
widgetData %>%  ggplot(aes(layer_height,mass,color=filament))+
  geom_point()+ scale_color_manual(values = c("green" = "green","red"="red"))

reg_m<-lm(mass ~ layer_height + filament,data=widgetData) #linear model

widgetData2<- widgetData%>% mutate(layer2 = layer_height^2)
reg_m2<-lm(mass ~ layer_height +layer2+ filament,data=widgetData2)
summary(reg_m2) #quadratic model

reg_mf<-lm(mass ~ as.factor(layer_height)+ filament,data=widgetData)
plot(reg_mf, which = 1)
# Remove filament as a variable:
reg_mf2<-lm(mass ~ as.factor(layer_height),data=widgetData)
summary(reg_mf2) # with as.factor()
plot(reg_mf2, which = 1)
```

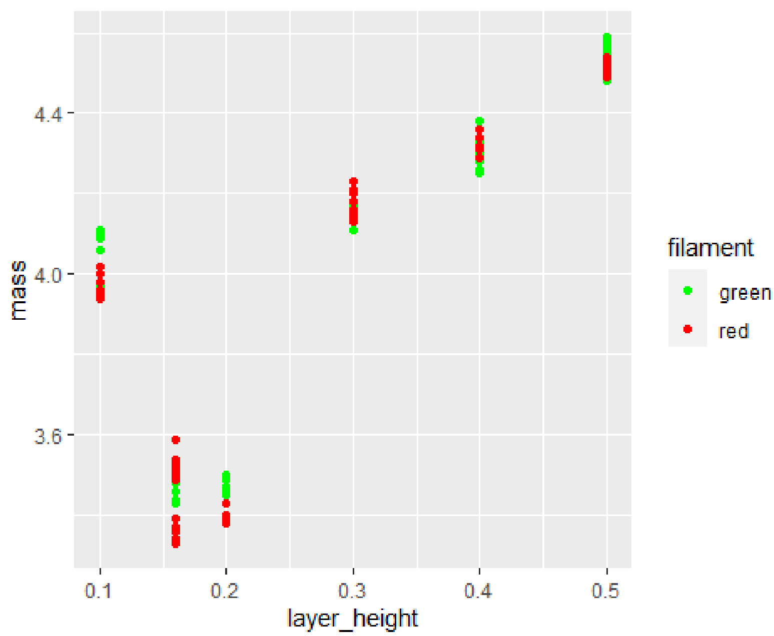


Fig. 10: Mass of each object, color-coded by filament, as function of layer height.

VI. ANALYSIS

Results for Standard Deviation (Quality of Build)

As hypothesized, the quadratic model for standard deviation (Model 2 in Table 1) is a better model than a linear (Model 1) model or null model. When a quadratic term is included in the GLM (layer_height*layer_height), the layer height coefficients show significance ($p < 0.05$) and the adjusted R^2 improves from 0.21 to 0.44. The quadratic curves are shown in Fig. 10.

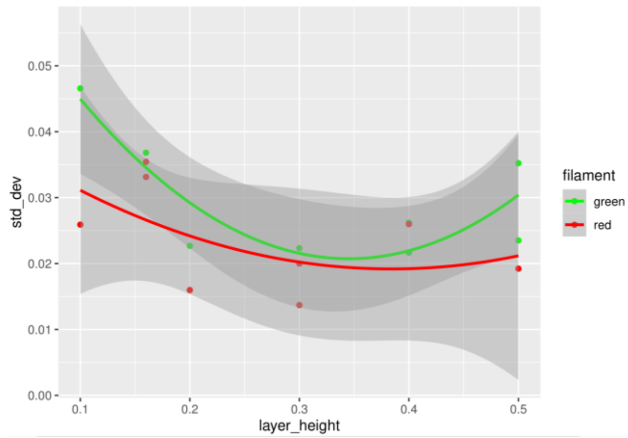


Fig. 10: Quadratic fits to the standard deviation of the batches

Table 1:

	Dependent variable:	
	std_dev	
	(1)	(2)
layer_height	-0.028^{*}	-0.195^{**}
	(0.014)	(0.067)
layer2		0.275^{**}
		(0.109)
filamentred	-0.007^{*}	-0.006^{*}
	(0.004)	(0.003)
Constant	0.038^{***}	0.058^{***}
	(0.005)	(0.009)
Observations	16	16
R^2	0.313	0.552
Adjusted R^2	0.207	0.440
Residual Std. Error	0.008 (df = 13)	0.007 (df = 12)
F Statistic	2.962^{*} (df = 2; 13)	4.922^{**} (df = 3; 12)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The following describes how to interpret the quadratic model (Model 2). The results show that the standard deviation of the mass of each batch decreases with an increase in layer height for small values of layer height, but increases with an increase in layer height at larger layer heights. Specifically, the standard deviation (y) depends on layer height (x) via the following:

$$y = \beta_{layer}\, x + \beta_{layer2}\, x^2 + (....),$$

with changes given by

$$dy = (\beta_{layer} + \beta_{layer2}\, x)\, dx.$$

For example, the model predicts that at x = 0.1 mm, increasing x to 0.2 mm changes the standard deviation by

$$(\beta_{layer} + 2\beta_{layer2} * x)(dx) = [-0.194668 \text{ g/mm} + 2*(0.274700 \text{g/mm}^2)*(0.1\text{mm})](0.1\text{mm})$$
$$= -0.0139 \text{ g}.$$

Assuming standard deviation is a good proxy for quality, this is expected if the advantage of better resolution is negated when the filament cannot extrude smoothly at very small layer heights or when the machine needs to make an excessive number of passes. The effect size seems reasonable, because the standard deviations themselves varied from about 0.01 – 0.05 grams.

Meanwhile, there is no evidence that changing to a red filament spool increases the standard deviation. The model predicts that going from green to red filament decreases the standard deviation by - 0.0063 grams. This is intended to be a one-sided hypothesis, so the fact that the coefficient is negative leads to a failure to reject the null hypothesis regardless of p-value. In sum, we fail to reject the null hypothesis that the red filament does not worsen quality.

The residuals of the model (Figure 11) seem randomly distributed. They are choppy due to small sample size (N = 16), but the model seems to be capturing the patterns appropriately.

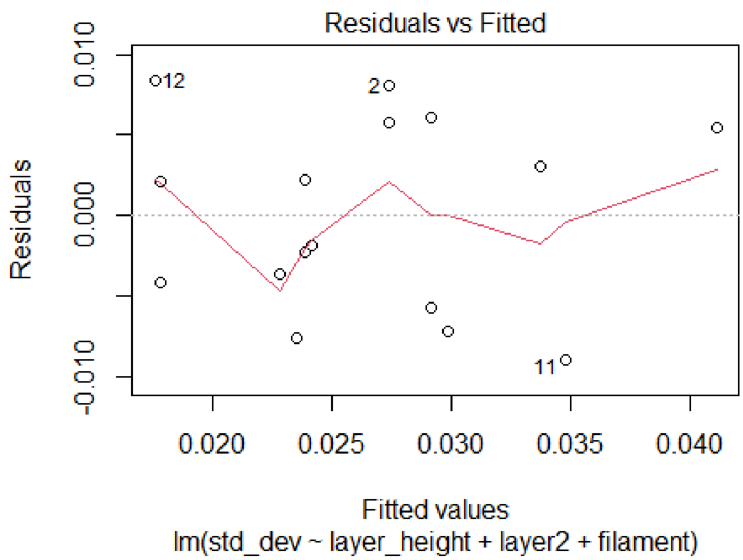


Fig. 11: Quadratic model for Standard Deviation

Results for Mass

The fit results for the mass of each object are shown in Table 2. Model 1 is linear (in layer height), Model 2 is quadratic, and Model 3 tests the effect of an interaction between layer height and filament color.

Table 2:

	Dependent variable:		
	mass		
	(1)	(2)	(3)
layer_height	2.324***	−0.486	2.192***
	(0.155)	(0.799)	(0.207)
layer2		4.668***	
		(1.304)	
filamentred	−0.035	−0.017	−0.122
	(0.043)	(0.041)	(0.100)
layer_height:filamentred			0.302
			(0.313)
Constant	3.373***	3.699***	3.416***
	(0.058)	(0.107)	(0.073)
Observations	141	141	141
R^2	0.635	0.666	0.637
Adjusted R^2	0.629	0.659	0.629
Residual Std. Error	0.248 (df = 138)	0.238 (df = 137)	0.248 (df = 137)
F Statistic	119.915*** (df = 2; 138)	91.052*** (df = 3; 137)	80.211*** (df = 3; 137)
Note:			*p<0.1; **p<0.05; ***p<0.01

Both the linear and quadratic models show a high degree of statistical significance for layer height as a predictor. This is because the minimum of mass in the quadratic model is shifted far to the left (smaller layer heights), so there is still an overall upward trend. If one knew nothing about the origin of the data, one would be tempted to apply the quadratic model; the linear model shows higher residual error and an adjusted R^2 slightly lower than the linear model (R^2_{adj} = 0.6295 vs. 0.6587). However, a visual inspection of the objects (Fig. 12) suggests a more nuanced interpretation. There is evidence that the lowest layer_height value should not be expected to follow the same pattern as the rest of the data.

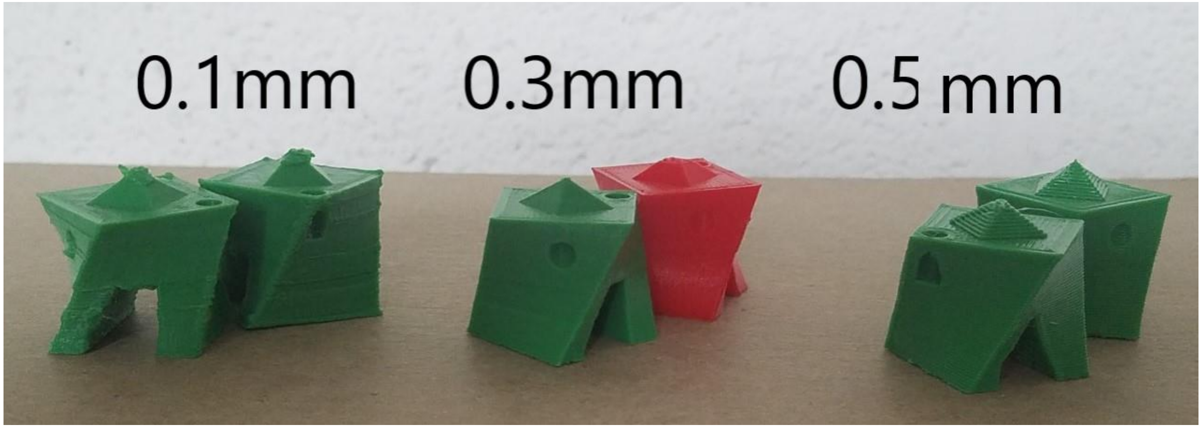


Fig. 12: The printers struggle to produce smooth objects at 0.10 mm layer height (left).

This layer height (0.10 mm) is smaller than the highest recommended resolution offered by the Qidi software (0.12 mm), suggesting that we may be pushing the resolution of the printer beyond its design limits. Visually, the objects printed with 0.10 mm appear rougher, with globs of filament at their pointed tips and bulging corners, whereas the objects printed at 0.16 mm are smoother and show no signs of blobs at the tips. One way to interpret this data is that increasing the layer height increases the mass of the object as long as one stays at or above 0.16 mm. The batches at 0.10 mm distort the overall patterns in the data. It is therefore not necessarily the case that the quadratic model is better; it will reduce residuals for the lower layer heights (light objects), but it might make worse predictions for larger layer heights (heavier objects), as shown by the residuals vs. fitted plots in Fig. 13.

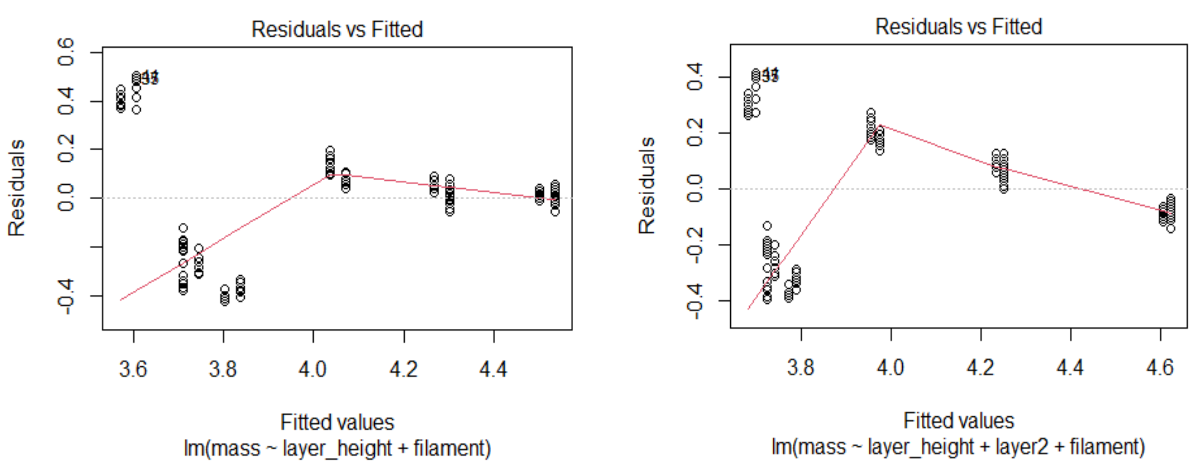


Fig. 13: Residuals for a linear model (left) and a quadratic model (right). Note the difference in vertical axes.

As an example of predicting the mass using regression, consider Model 1. One can predict the effect on mass of changing the filament to red or going up 0.1mm in layer height, as follows:

- Effect due to switching to red

The model predicts switching to red filament decreases mass by -0.03478 g. This is a two-sided hypothesis, so the confidence interval is as follows:

True mass for red = estimated_value +/- 1.96*se, or

-0.03487 g +/- 1.96*0.04263 g = - 0.12 g to 0.05 g.

So in fact, the actual effect of switching to red may be either an increase or a decrease in the mass. The effect of changing the filament is not statistically significant at the 0.05 level.

- Effect due to 1mm layer increase in height

The table shows that a 1 mm layer height increase will increase mass by 2.32449 g. This is a two-sided hypothesis, so we have the following interpretation:

True mass for a one-gram increase in layer height = estimated_value+1.96*se, or

2.32449 +/- 1.96*0.15540 = 2.02 g to 2.63 g

This confidence interval is plausible, since increases that are in 0.1 mm increments seem to increase the mass by less than 0.5 g, looking at the plot.

- Power Analysis

If one was going to design a study to predict mass for future work, one could use these preliminary results to select a sample size, given a desired power (say 0.8):

```
library(pwr)

Rsq_RG <- 0.6348 #R^2 for regression on 2 indep variables, filament and layer
_height
#calculate the sample size (N) from v = N - p for desired power of 0.8
F2 <-  Rsq_RG/(1-Rsq_RG)
k <- 2 #number of indep. variables = df of numerator ("u")
p <- k + 1 #number of predictors (including the intercept)
pwr.f2.test(u = k, f2 = F2, power = .8, v = NULL)$v + p

## [1] 9.287702
```

The required sample size turns out to be 10 objects. Our study (N = 159) is over-powered! In addition, one probably could have gotten a better R^2 value, and thus achieved the same results with a smaller sample, by eliminating the 0.1mm layer height category. Our data would be more linear in that case.

Eliminating filament as a variable would also improve the power. Since there is not expected to be any interaction between filament and layer height, we could get quite a good idea of the effect of layer height by always using the same filament spool. Indeed, consulting the regression results for Model 3 in Table 2, the interaction term of filament*layer_height gives $p > 0.05$.

A Better Model?

The problem with both the linear and quadratic approaches is that the patterns in the actual data are not captured by either one, as seen by the plots of residuals (Fig. 13). The residuals show that certain layer heights are consistently over or underestimating the mass. It is apparent just from looking at the graph of mass vs. layer_height that a second-degree polynomial is not going to describe the data well. One solution to this would be to eliminate the 0.1mm layer height and fit the remaining data. This would provide much better prediction for the data above 0.1mm. Another approach is to treat layer height as categorical and use as.factor() in the fit. This is shown in Table 3, both with and without filament color as a variable.

The use of factors improves the predictive power of the model; the R^2 has increased to 0.99. Layer height is predicted of mass at high confidence ($p < 0.01$).

The results show that one can predict the mass of a printed object, given the layer height, with a high degree of certainty. The model that includes the filament variable finds that filament is statistically significant. This significance is spurious; it is an artifact of the batching – every object in a batch has the same filament color. With a low number of batches per category, random drifts in the mean mass of batches makes filament appear significant. We have seen enough evidence so far to conclude that the red filament is not defective and this is probably not a real effect. Therefore, in predicting the mass, it would make more sense to use a univariate regression that excludes filament color.

Table 3:

	Dependent variable:	
	mass	
	(1)	(2)
as.factor(layer_height)0.16	-0.564^{***}	-0.567^{***}
	(0.014)	(0.014)
as.factor(layer_height)0.2	-0.589^{***}	-0.589^{***}
	(0.015)	(0.016)
as.factor(layer_height)0.3	0.150^{***}	0.147^{***}
	(0.013)	(0.014)
as.factor(layer_height)0.4	0.293^{***}	0.298^{***}
	(0.014)	(0.014)
as.factor(layer_height)0.5	0.509^{***}	0.513^{***}
	(0.014)	(0.014)
filamentred	-0.022^{***}	
	(0.008)	
Constant	4.031^{***}	4.019^{***}
	(0.011)	(0.011)
Observations	141	141
R^2	0.988	0.987
Adjusted R^2	0.988	0.987
Residual Std. Error	0.045 (df = 134)	0.046 (df = 135)
F Statistic	$1,850.254^{***}$ (df = 6; 134)	$2,117.891^{***}$ (df = 5; 135)
Note:		*p<0.1; **p<0.05; ***p<0.01

- Prediction

As an example of interpreting the regression results, consider the model without filament color, and generate the predicted masses for 0.10 mm and 0.16 mm. We expect the latter to be lower, and indeed one finds that:

$\widehat{mass}$(x = 0.1mm) = β_0 = 4.031 g.

$\widehat{mass}$ (x = 0.16mm) = $\beta_0 + \beta_{0.16}$ = 4.031 g – 0.564 g = 3.467 g.

The disadvantage of treating layer height as categorical is that the predictions are only valid for one of the layer height values already in the data set. If we wanted to predict the value of mass at x = 0.25 mm, we would need a model that does not treat the layer height as a factor.

VI. CONCLUSION AND FUTURE OUTLOOK

From the standard deviation data, we fail to reject the null hypothesis for the effect of filament; it would appear that the red filament is not, in fact, defective. However, when it comes to layer height, we reject a null model and advocate for a quadratic model. While the manufacturer labels 0.12 mm an "extra fine" resolution, calculating the minimum of the standard deviation vs. layer height model gives $x_{min} = 0.354$ mm. Using a smaller layer height than this may minimize the visual "step" effect, but it does not give a more consistent product.

In modeling the dependence of mass on layer_height, the results in aggregate supported the alternative hypothesis that thickening the layers changed the mass. This effect was significant. In retrospect, this may be a measurable effect because while most of the *volume* is infill, and the bottoms/tops are only a small proportion of the overall layers, at 20% density each inner layer is not contributing much to the mass. Thickening the bottom and top layers thus has a significant effect. However, the smallest layer height studied, 0.1 mm, violates the pattern and shows a higher mass than the next layer height level. When developing a regression model to predict the mass, including data from the objects printed with layer heights smaller than recommended by the manufacturer distorts the overall patterns in the data and decreases the accuracy of the predictions. If a prediction is desired for one of the layer heights used in this study, best results are obtained from a factor model.

In the linear and quadratic models, there was no evidence that the filament used predicts the mass, as expected. In the factor model, the filament appears to have predictive power, but that is probably an artifact of the batching process.

Given the way this dataset was generated, any skepticism regarding causality would center on methodology and omitted variable bias rather than any question of which way the causality works. The independent variables of filament and layer height are clearly independent variables, as they are manipulated directly. The data supports a causal link between increasing layer height (at least for values at or above 0.16 mm) and increasing the mass of the object, and a mechanism for that pattern has been described above. There is also plausible mechanism for why very low and very high layer heights would produce more variable output (higher standard deviation), and lower quality.

However, some puzzles in the data suggest the presence of omitted predictors. In particular, the variation between the mean mass of batches, even with identical independent variables, in some cases seems to exceed the variation within each batch. A hidden effect of bed-leveling / misalignment could explain this variation. On a single printer, the alignment could drift over time, or be affected by human fiddling. There could also be slight differences in leveling/alignment between printers.

Future experiments could improve methodology. Specifically, one should be confined to a single printer, disallow bed leveling procedures within the experimental duration, use a single spool of filament (unless comparing different types of plastic), and restrict layer thickness to 0.12 mm and above (unless one is particularly interested in probing layer heights beyond the extruder's design capabilities. In addition, a protocol for shuffling the variation of the independent variable so that it would not correlate with the trial number would help eliminate omitted variable bias. It would also be interesting to try varying printer speed and/or object orientation.

Furthermore, to improve the mathematical modeling of mass, sampling more layer heights would be helpful. One could hypothesize that the effect of layer height on mass disappears as the percentage infill approaches 100%.

Overall, this topic shows promise for future regression projects.

References

[1] Holmes and Wieman , Physics Today 71, 1, 38 (2018); https://doi.org/10.1063/PT.3.3816

[2] Jalil, J. M. N., Alvarez, E. R., Garcia, I. R. K., Almaguer, S. P., & 2020 IEEE Global Engineering Education Conference (EDUCON) Porto, Portugal 2020 April 27 - 2020 April 30. (2020). 2020 ieee global engineering education conference (educon). In Work in progress: design and construction of physics laboratory equipment and an authentic evaluation system as a pedagogical tool in the integral training of engineering students (pp. 1471–1477). essay, IEEE. https://doi.org/10.1109/EDUCON45650.2020.9125294

[3] Flynn, E. P., Bach, C., & 2019 IEEE Technology & Engineering Management Conference (TEMSCON) Atlanta, GA, USA 2019 June 12 - 2019 June 14. (2019). 2019 ieee technology & engineering management conference (temscon). In Integrating advanced cad modeling simulation, 3d printing, and manufacturing into higher education stem courses (pp. 1–5). essay, IEEE. https://doi.org/10.1109/TEMSCON.2019.8813627

[4] W. M. Wang,C. Zanni,L. Kobbelt, Improved Surface Quality in 3D Printing by Optimizing the Printing Direction, Computer Graphics Forum, Volume 35, Issue 2 p. 59-70. https://onlinelibrary.wiley.com/doi/full/10.1111/cgf.12811

[5] Vaezi, M., Chua, C.K. Effects of layer thickness and binder saturation level parameters on 3D printing process. Int J Adv Manuf Technol 53, 275–284 (2011). https://doi.org/10.1007/s00170-010-2821-1

[6] Nadir Ayrilmis, Effect of layer thickness on surface properties of 3D printed materials produced from wood flour/PLA filament, Polymer Testing, Volume 71, 2018, Pages 163-166, ISSN 0142-9418, https://doi.org/10.1016/j.polymertesting.2018.09.009.