Fruit Ripening Project

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Introduction

Our research question was to see whether the presence of different fruits would ripen bananas quicker. Specifically, we tested whether having an apple, a cucumber, or both near bananas would lead to more ripe bananas. To set up our experiment, we bought 2 apples, 2 cucumbers, and 2 bunches of bananas (12 bananas total). The bananas that were bought were all unripe and relatively the same in terms of peel color. This last part was confirmed by the average RGB pixel values taken from pictures of the bananas, the process of which we will describe later. We then randomly partitioned the bananas into 4 groups of 3 and each group was put into a desk drawer in WH 436. The first group had an apple added to the drawer, the second group had a cucumber, the third had an apple and a cucumber, and the last was the control. We ran this experiment for a total of 5 days. Now that we have the experiment set up, we will now discuss how we measured ripeness. We decided to focus on 2 factors to measure ripeness: peel color and firmness. Through our collective experiences with bananas, we knew that as they ripen, they get softer and their peel becomes darker and less green. Thus, the firmness was recorded by having a group member rate the hardness of the banana on a scale from 1 to 5. The group member was blind to which banana they were measuring and this was done on the first and last day of the experiment. For peel color, we decided to take pictures of the peel to analyze the average pixel values. Over the five days, we took pictures of each banana at around the same time of day in a place where there was not much natural light. We used flash to control lighting and held the camera a similar distance from the bananas while taking the pictures. To analyze these pictures, we used an edge detection algorithm to detect the edge of the banana from the background and then set the background to pure black. Each picture was also manually inspected to set any remaining background to pure black. Then, we iterated through each pixel in the picture and discarded any pure black value. After inspecting a subset of photos, we were able to see the number of pixels in the banana that were discarded was negligible if any at all. The non-discarded pixels were then averaged to get a single RGB value for each picture. This green value is the one we will use in later analyses. We also calculate the magnitude of the average RGB values by taking the 3D Euclidean distance of our RGB from (0,0,0). We do this since we can think of RGB values living in a 3D space and the closer we get to (0,0,0), the closer to black the RGB value is. The code for this is available on our github repository.

Figure 1: Original (left) and Processed (right)

Analysis on Softness

Recall, for each banana we measured the firmness on a scale from 5 (firm) to 1(soft) on the first and last days of the experiment. The change in for each banana along with treatment assignment is presented below.

Banana	Treatment	Change in Firmness
1	0	2
2	0	2
3	0	2
4	1	2
5	1	2
6	1	1
7	2	3
8	2	1
9	2	3
10	3	3
11	3	2
12	3	1

We will perform two separate analyses on this data. In the first, we will compare each treatment group to the control group using a permutation test with null hypothesis $H_0 :=$ *treatment assignment has no effect on change in firmness.* With alternative hypothesis $H_A :=$ *treatment assignment has a positive effect on change in firmness.* We will use the difference in means test statistic: $T = \mu_{Firmness} - \mu_{Treat}$. Note one problem, every banana in the control group had an equal change in firmness. Due to this and the low sample size these tests will have low power with a minimum p-value of 0.14. When running this analysis we get the following p-values for each treatment group:

Group	Apple	Cucumber	Apple + Cucumber
p-value	0.5	0.5	0.7

The second analysis we run we test to see if any of the treatments/control have any significant effect relative to one another. The null hypothesis is again: $H_0 :=$ *Treatment assignment has no effect on change in firmness* while the alternative hypothesis is the following: $H_a :=$ *there are treatmentswhich have a significant difference in change in firmness relative* The test statistic we use is the F-statistic, which is given by

$$F := \frac{\textit{between group variability}}{\textit{within group variability}}$$

Permutation tests on relative change between first and the last day

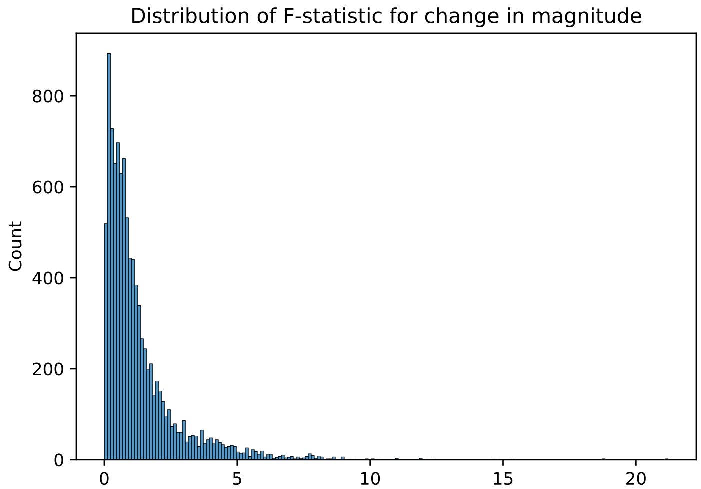
Let us define M_{ij} to be the magnitude of pixel for i^{th} banana on j^{th} day of the experiment. Since we ran the experiment for 5 days, we have $j \in \{1, 2, 3, 4, 5\}$. In this section, we study the variable

$$\Delta M_i := M_{i1} - M_{i5},$$

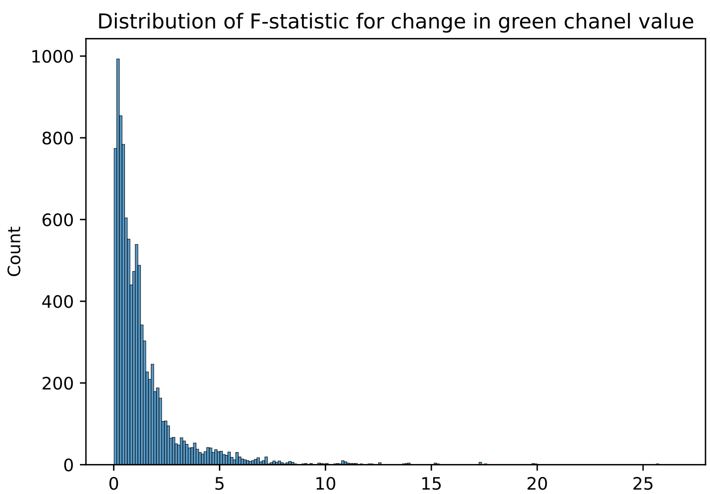
that is the change in pixel magnitude between the first and the last day of the experiment for each banana. Similarly, let us denote G_{ij} to be the average green channel value for i^{th} banana on j^{th} day of the experiment. Then, we can define

$$\Delta G_i := G_{i1} - G_{i5}.$$

First, we begin by studying if there exist any pair of groups, either treatment-control pair or treatment-treatment pair, for which ΔM_i or ΔG_i is statistically different across these two groups in the pair. For this, we use a permutation test using F-statistic as the test statistic. Since we have 12 observations across four groups, computing the p-value requires computing test statistics for 12! permutations, which is infeasible. So, we compute our p-value using 10000 randomly generated permutations. The figure below shows the distribution plot of the test statistic under the null hypothesis. Note that the test statistic is always positive, so our test is one-sided.



We repeat the same F-statistic based permutation test for variable ΔG as well.



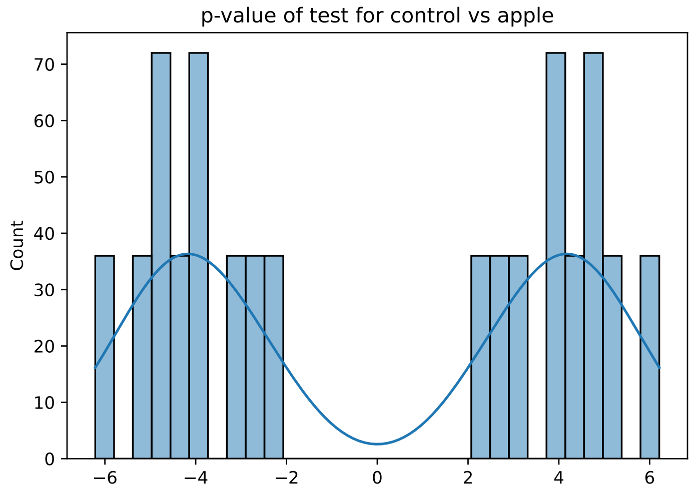
The summary of our tests for both of these variables is presented in the following table.

Variable	F-Statistic	p-value
ΔM	5.62	0.02
ΔG	4.84	0.04

Since the p-value is < 0.05 for both variables ΔM and ΔG, our tests suggest that there is at least one pair of groups between which the treatment effect is significant. Next, we do permutation test on each pair of group separately using difference in means as our test statistic.

For instance, the following plot shows the distribution of test statistics while comparing the control group to the treatment group 1 (apple) under the sharp null hypothesis. Since we obtain a p-value to be 0.7, we conclude that the treatment of apple does not have a statistically significant treatment effect.

```
## p-value 0.7
```



The p-value of all the tests, where each test compares a treatment group with either control or another treatment group, is summarized in tables below.

	Control	Apple	Cucumber	Apple & Cucumber
Control	-	0.2	0.05	0.1
Apple	-	-	0.05	0.4
Cucumber	-	-	-	1.03
Apple & Cucumber	-	-	-	-

Table 4: p-values for variable ΔM

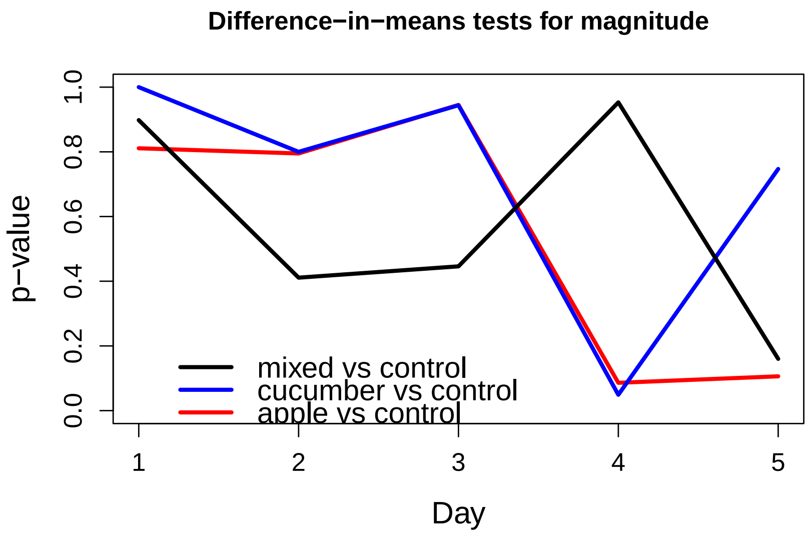
	Control	Apple	Cucumber	Apple & Cucumber
Control	-	0.7	0.05	0.3
Apple	-	-	0.05	0.1
Cucumber	-	-	-	0.9
Apple & Cucumber	-	-	-	-

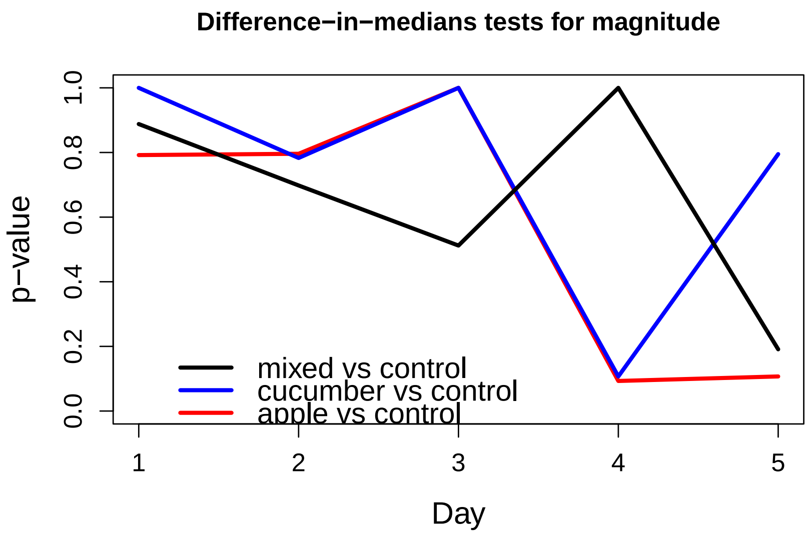
Table 5: p-values for variable ΔG

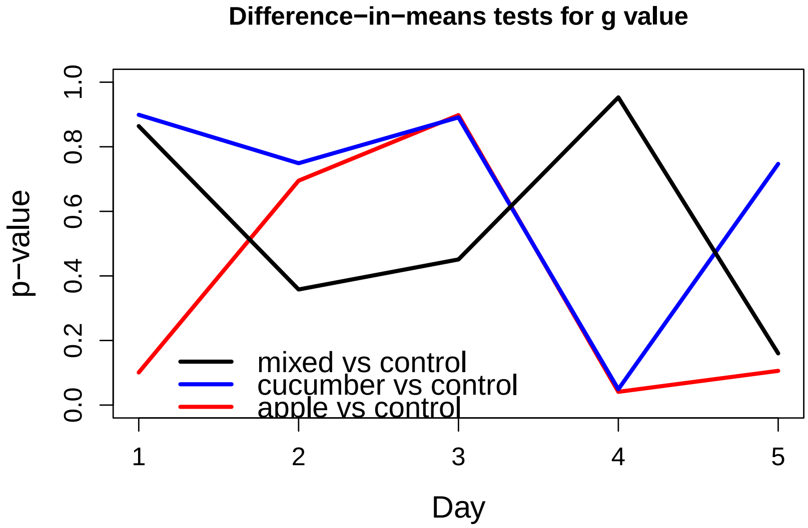
As we can see, the p-values of the cucumber treatment group, when compared against the control and apple group, have p-value 0.05. However, we want to point out that our cucumber was rotten and the bananas got soaked in rotten cucumber juice. We believe that the low p-value was possible because soaked bananas looked darker compared to other bananas. Nevertheless, even with a 0.05 p-value, after multiple testing adjustments, none of the treatments will be significant. Therefore, based on our analysis above, none of our treatments is significant. That is, we did not find any statistical evidence that any of these methods quickens the ripening process.

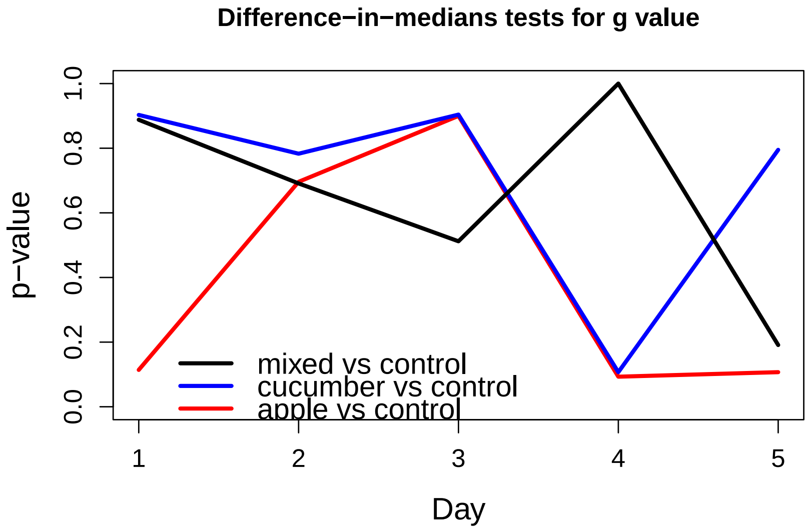
Permutation tests on consecutive days

We are also interested in whether each of the treatments accelerates the ripening on each of the five days. We consider four combinations of permutation tests: (1) permutation test on RGB magnitude by difference-in-means; (2) permutation test on RGB magnitude by difference-in-medians; (3) permutation test on RGB green value by difference-in-means; (4) permutation test on RGB green value by difference-in-medians. The permutation is implemented on the treatments of 6 bananas, three of which is in the control group and the other three in a treatment group. For each test, we have 3 p-values for 3 'treatment v.s. control' groups on each of the five days. The results are summarized in the following plots:









As shown in the figures, there is no significant ripening effect among the treatments on each day.

Permutation tests on Repeated Measurements

Given the unexpected incident on the 3rd treatment group at last two days, we would like to see over the course of experiments, if there is any positive treatment effect comparing one to the other, or there is any treatment effect among the 4 groups.

We first compute the Lag 1 difference of the RGB magnitude and Green RGB value for each day, and observe that the first day measurement is much larger comparing to others. To be cautious of the outliers, we choose to work with median-based test statistics.

To compare any two pairs of the groups, we subset the data and use difference in median. We conduct 1-sided permutation test by randomly permuting 10,000 times of treatment assignments (fixed for each of the days). By doing so, the subject variability stays constant for each of the permutation, but variability owing to design is captured.

		Control	Apple	Cucumber	Apple & Cucumber
	Control	-	0.1441	0.2495	0.2513
H	Apple	-	-	0.7499	0.6548
	Cucumber	-	-	-	0.4381
	Apple & Cucumber	-	-	-	-

Table 7: p-values for green

None of the tests are significant for RGB magnitude and Green RGB before multiplicity adjustment, where the group in row is the group we compared to for each of the column.

	Control	Apple	Cucumber	Apple & Cucumber
Control	-	0.3924	0.3521	0.3504
Apple	-	-	0.4953	0.7097
Cucumber	-	-	-	0.6973
Apple & Cucumber	-	-	-	-

Table 6: p-values for magnitude

To test the presence of any treatment difference comparing each to the other, we use between-sample variability / within-sample variability of median as test statistics, where

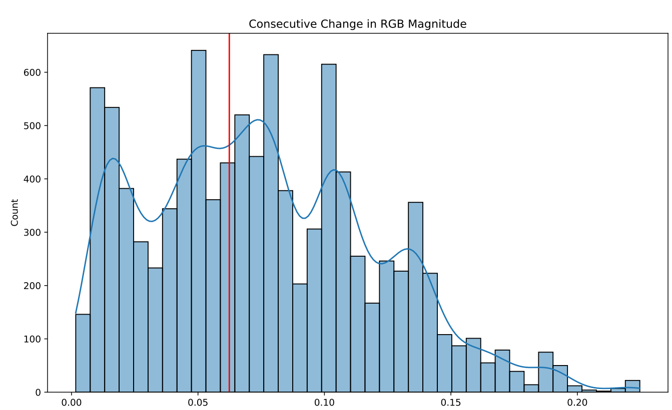
$$F_{med} = \frac{\frac{1}{4-1}\sum_{j=1}^{4} 3\left(\tilde{y}_j - \tilde{y}\right)^2}{\frac{1}{12-4}\sum_{j=1}^{k}\sum_{i=1}^{3}\left(y_{ij} - \tilde{y}_j\right)^2}.$$

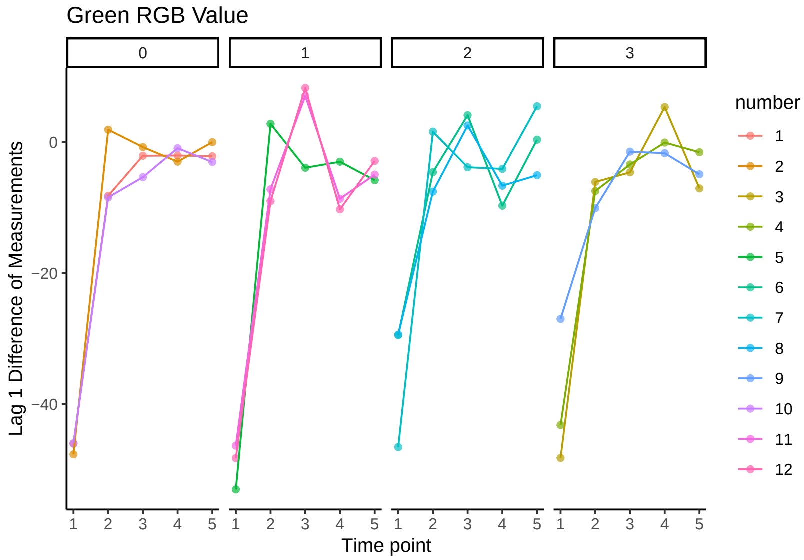
We randomly permute treatment assignment for 10,000 times (fixed across days). The p-value for RGB magnitude is 0.9188 and o-value for Green RGB is 0.5844. None of the test is significant.

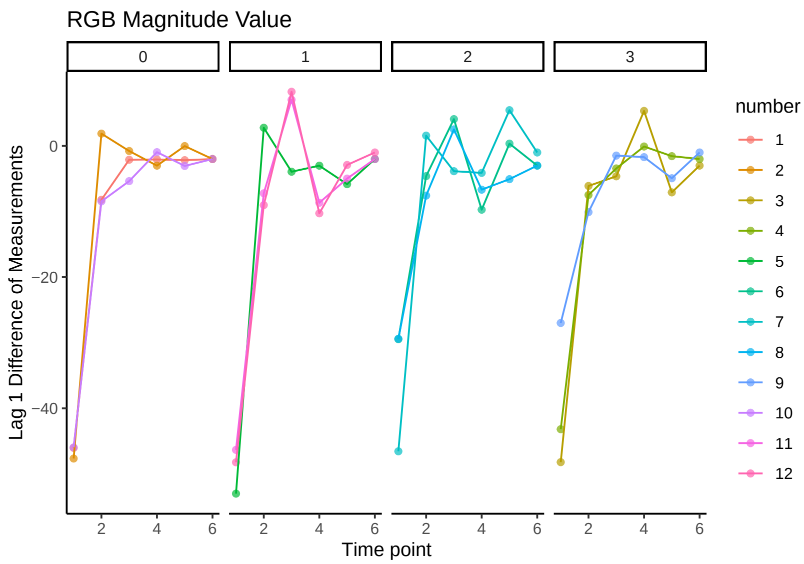
It is important to note that the current analysis result is constraint by the small sample size of the experiment we ran.

```
## ' We use normalised (divide by magnitude) green RGB value for each of the data point,
```

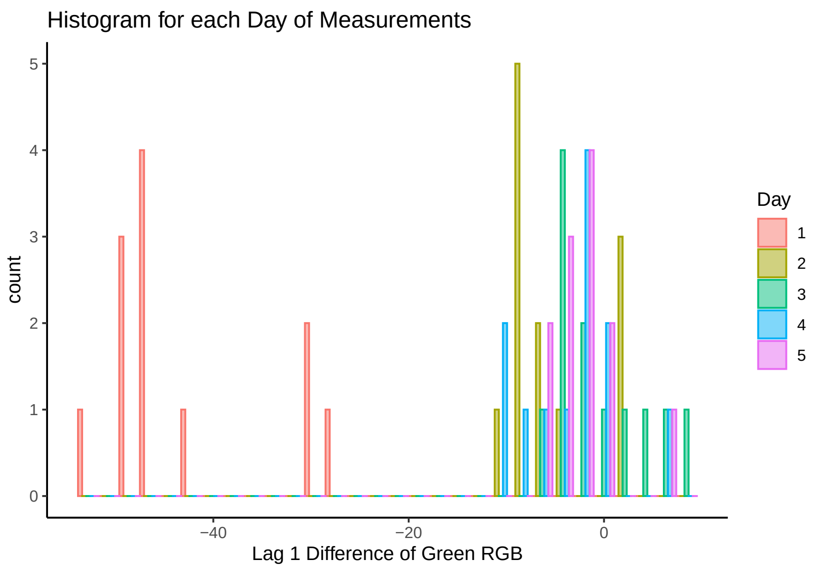
```
## obs stats var_median 0.062387645
```



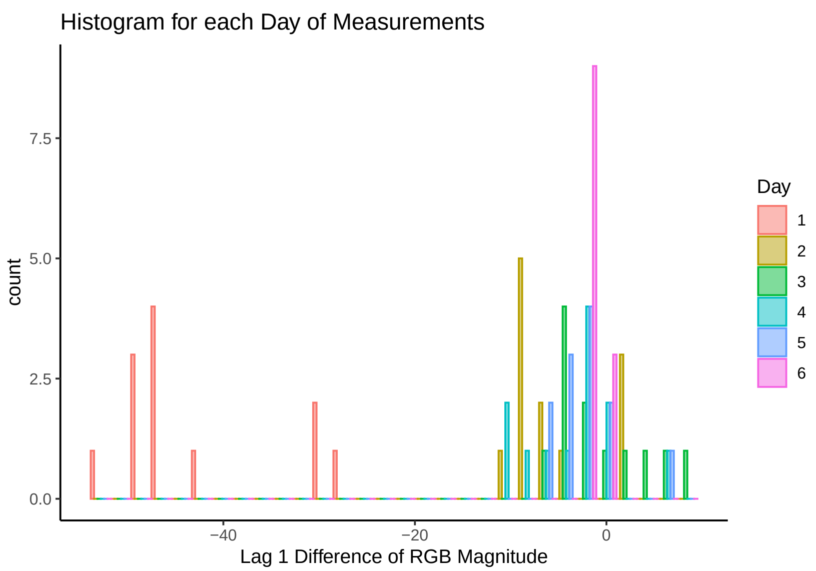





```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



Conclusion