Low-cost Perceptual Approximations of Subsurface Scattering

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Rendering translucent objects like leaves and glue is computationally expensive. Previous work suggests that in some cases the human visual system can not discriminate physically based subsurface scattering from low-cost approximations. This study investigates three such methods and evaluates them in a psychovisual experiment. We find that all three methods can, to some extent, increase the perception of SSS. The High-Pass Inversion and Gassian Background Texturing methods seem the most promising. Although, high variance in the results indicate limitations in the methods used.

CCS Concepts: • **Computing methodologies → Perception**; Image processing; **Image-based rendering**.

Additional Key Words and Phrases: Subsurface, Scattering, Rendering, Realtime, Image, Processing

1 Introduction

Many complex objects in our world like fruit slices, cheese and human skin are translucent. These complex objects have a characteristic glow when held up to light as seen in Figure 1. This glow results from subsurface scattering (SSS) of light.

Accurately rendering complex translucent objects is important for creating photo-realistic scenes. Unfortunately, the graphics methods required for rendering these objects differ from simple semi-transparent objects like coloured glass. Lowering the alpha value as one would for coloured glass does not reproduce the characteristic glow produced by computationally expensive SSS methods.

It is generally believed that the visual system is capable of performing reverse optics to identify intrinsic material properties (e.g. albedo). Opacity constancy is the ability for a visual system to perceive constant opacity in varying lighting conditions. Fleming and Bülthoff [2005] find, by varying lighting conditions in a psychovisual experiment, that SSS is too complex for the visual system to perform reverse optics and it therefore fails to obtain opacity constancy. Moreover, they suggest that the visual system must rely on simple image statistics in its perception of translucency. This suggests that fast methods could exist that convincingly approximate the perceptual effect of SSS without expensive computation.

In this paper, we evaluate the perception of multiple low-cost methods that approximate the effect of SSS in a psychovisual matching experiment. We answer the research questions:

How do low cost approximations of SSS affect the perception of translucency?

2 Methods

Based on the result that the visual system cannot perform reverse optics for SSS, we give three computationally low-cost methods for transforming opaque rendered objects (i.e high opacity) into translucent objects (i.e low opacity).

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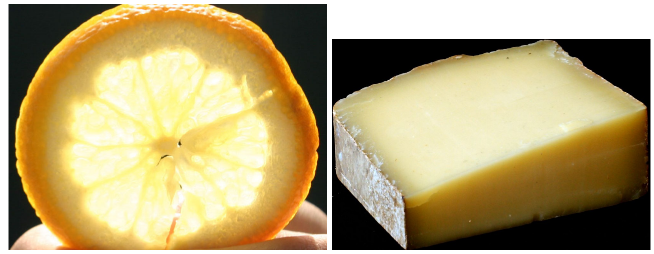


(a) Orange slice (flickr.com). The flesh of the fruit glows due to SSS from light behind the slice.

(b) Comte cheese (wikipedia.com). There is a glow on the front side of the cheese block that forms through SSS.

Fig. 1. Photographs of complex translucent objects

2.1 Histogram Matching (HM)

Fleming and Bülthoff [2005] argue that image contrast[1] is the most important cue in opacity perception. Figure 2 shows how intensity distribution varies with translucency. Objects that appear more translucent have more spread out intensity histograms. The simplest method the authors present involves transforming the intensities of an opaque image such that the histogram resembles that of a translucent object.

2.2 High-Pass Inversion (HPI)

We present an adapted version of an image processing pipeline by Fleming and Bülthoff [2005] that we will refer to as High-Pass Inversion (HPI). First, we start with a mask of the object i.e an image that is 1 if the corresponding pixel contains the object and 0 if it does not. Then we take a highpass filter of this object and invert the result.

We pass the original image through a high-pass filter with a low parameter cutoff frequency of $f_{hp} = 3$ cycles per image width. Then we invert the colours. This produces some shadows typical of SSS objects. Then we linearly combine the shadows with the original image weighted by a parameter $w_{lc} = 0.25$ meaning $\frac{1}{4}$ is the original image and $\frac{3}{4}$ are the shadows. Finally, we histogram match the result like in the HM method. This pipeline is demonstrated in Figure 3.

2.3 Gaussian Background Texturing (GBT)

So far all the cited methods work against a black void background. While not strictly needed[Fleming and Bülthoff 2005], the surroundings can also give the visual system context for translucency detection. Khan et al. [2006] find that an object can be made to appear translucent by texturing it with the background convolved with a Gaussian filter. An example of this method can be seen in Figure 4

[1]Fleming and Bülthoff [2005] do not commit to a single definition of contrast but rather use the term loosely and focus more on intensity histograms.

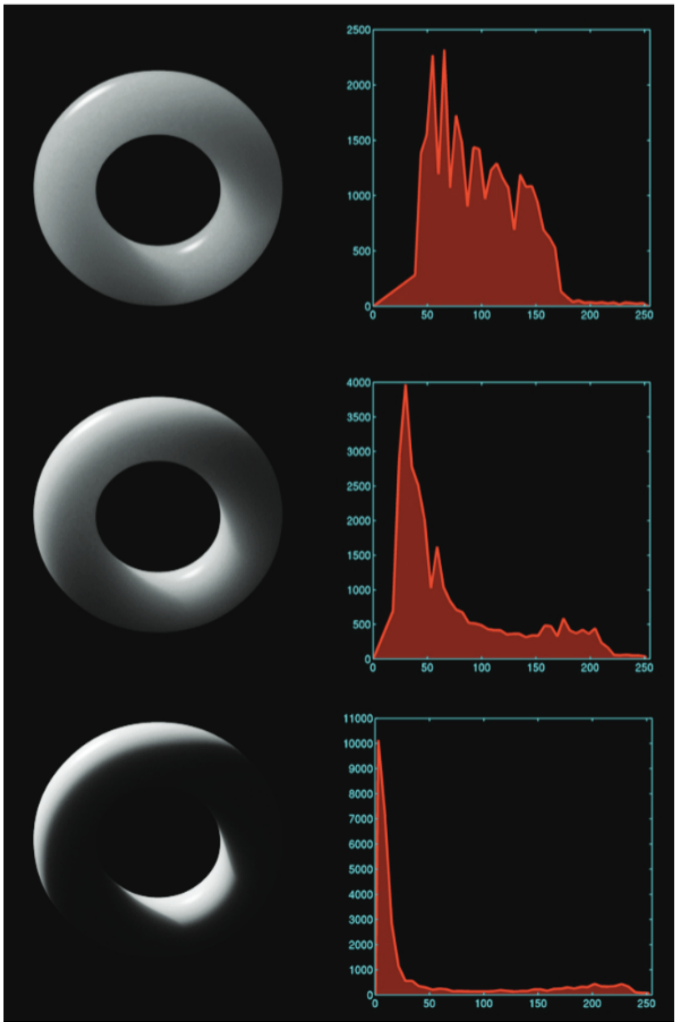


Fig. 2. Three rendered toruses and their corresponding intensity histograms all rendered with SSS simulation, ordered from most translucent (top) to least translucent (bottom). [Fleming and Bülthoff 2005]

3 Experimental Setup

We measure the effect on the perception of translucency when using the three aforementioned low-cost SSS approximations in a psychovisual experiment. This is accomplished using a method of adjustment experiment for perceived translucency. The aim is to show that participants indicate that the presented methods produce images that are significantly more translucent than a totally opaque object.

3.1 Scene Description

The subject is one of two objects: a torus and the Stanford Dragon[2]. There is a single point light source behind the torus and dragon. This is because SSS is easier to detect when light is behind the object[Fleming and Bülthoff 2005; Lanza et al. 2022]. The background

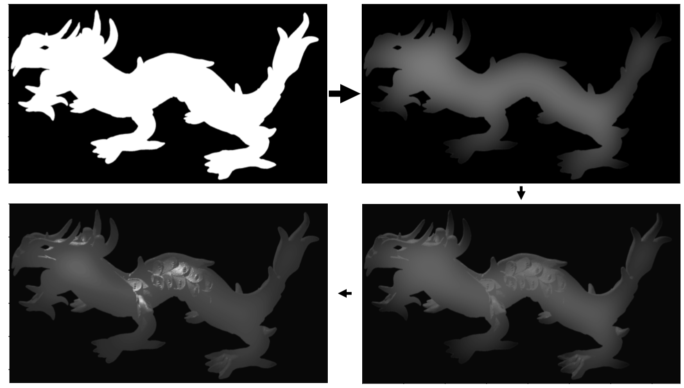


Fig. 3. HPI Pipeline. Top right is the mask. Top left is the inverted high pass filter. Bottom right is the linear combination. Bottom left is the final output after histogram matching.

Fig. 4. GBT example. Left is dragon textured with background. Right is dragon textured with Gaussian filter of background

is a black void or an image. When testing the GBT method, we only use a background image since it cannot be performed in a black void.

3.2 Stimulus

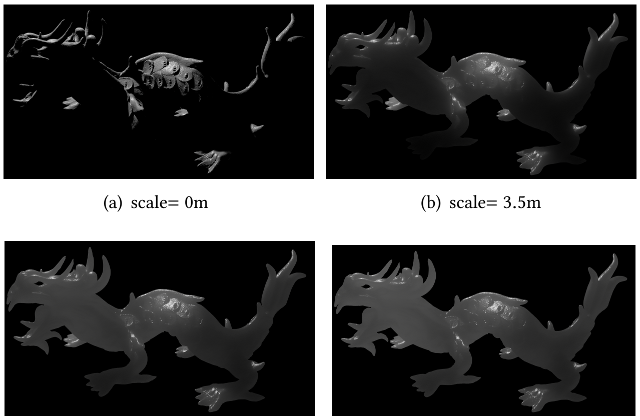
We present participants with one stimulus at a time. We permute every object type rendered with every possible method behind every background type. This results in 2 objects $\times$ 2 methods $\times$ 2 backgrounds $+$ 2 objects $\times$ 1 GBT method $\times$ 1 background = 10 total stimuli. The stimuli will be displayed in a random order. A grey screen is displayed for 3 seconds in between stimuli so that previous stimuli do not influence the participants' answers.

3.3 Method of Adjustment

We render a reference image of the same object as in the stimulus with high-cost SSS techniques at 100 uniformly spaced subsurface component *scales*[3]. Four example renders are given in Figure 5. These images can be selected with a slider. Participants need to match the stimulus opacity with the reference opacity as close as possible. The weight that they choose will be considered as the level of opacity they perceive in the image. This produces a value from 0 meaning no SSS and opaque to a maximal value (see Footnote 3)

[2]https://graphics.stanford.edu/data/3Dscanrep/

[3]Using the *Principled Shader* in Blender. There are two important parameters *weight* and *scale* that affect translucency. We choose $weight = 1.0$ and *scale* will range from 0 to some maximum hand-chosen value since increasing it too high will make the object appear opaque again



(a) scale= 0m

(b) scale= 3.5m

(c) scale=7m

(d) scale=10m

Fig. 5. Slider for method of adjustment for dragon object type

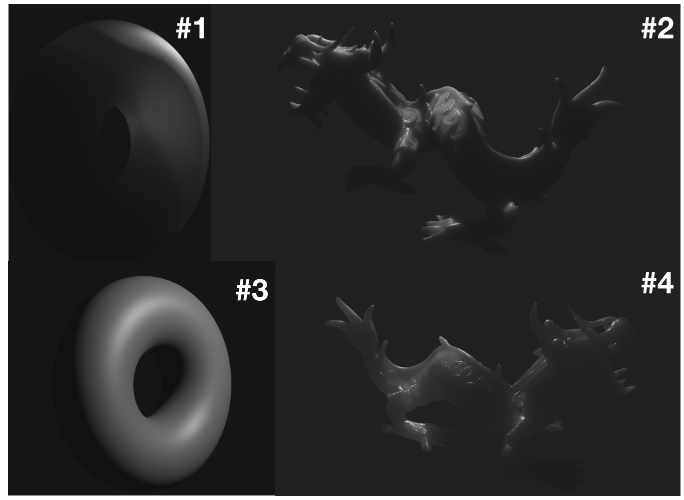


Fig. 6. Tutorial images. #1 rendered with *scale* = 7.6, #2 *scale* = 0.5, #3 *scale* = 0.0, #4 *scale* = 3.0

meaning maximally translucent and very bright SSS. Note that this value is not perceptually calibrated.

3.4 Experiment Interface

The method of adjustment setup was implemented as a website[4]. The website contains an introductory explanation of SSS and the participants' task.

3.5 Tutorial Images

Before being shown the stimuli participants are shown four tutorial images as warm-up. These can be seen in Figure 6. These images are from a different angle than the rest of the images to require the participants to think about SSS in the beginning a not choose the picture that looks identical.

This lets participants become familiar with the test setup and allows us to quantify that participants understand the task.

4 Results

The experiment had $n = 18$ participants. They took on average 12 minutes to complete the experiment. All the stimuli and the responses of the participants as box-plots[5] are given in Figures 7,8,9 and 10.

4.1 Basic Observations From Result Data

The median *scales* of all the tested low-cost SSS methods are much higher than 0. The interquartile ranges (IQR) of *scale* of all the tested low-cost SSS methods are quite high.

The median and IQR of *scale* for HM is higher than HPI for the stimuli with a background of a black void Figures 7,8. The median and IQR of *scale* for GBT is lower than for HM and HPI in the cases with a background image Figures 9,10.

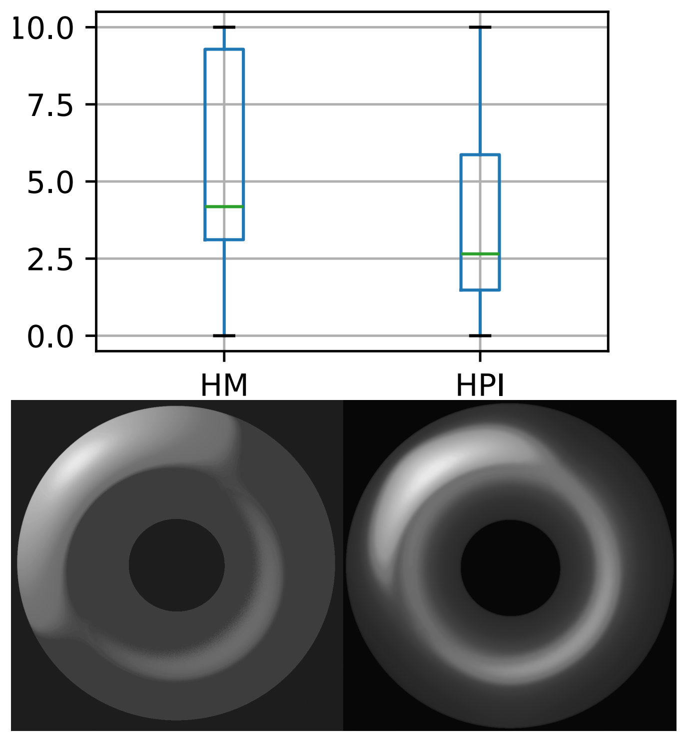


Fig. 7. Response to low-cost SSS toruses with black void background

4.2 Statistical treatment

There are three categorical independent variables: object type, SSS methods, and background type. There is one scalar dependent variable: the perceived translucency.

Every stimulus is produced by performing some transformation on the object with $scale = 0$. We are interested in whether the

[4] https://robynsb.github.io/translucencymatcher/experiment/

[5] For all the box-plots, the box extends from the first quartile to the third quartile of the data, with a line at the median. The whiskers extend from the box to the farthest response lying within 1.5x the inter-quartile range from the box. The circles indicate all data points outside of the whiskers. Note that the scale changes in between box-plots, the given scale represents the whole range for each situation.

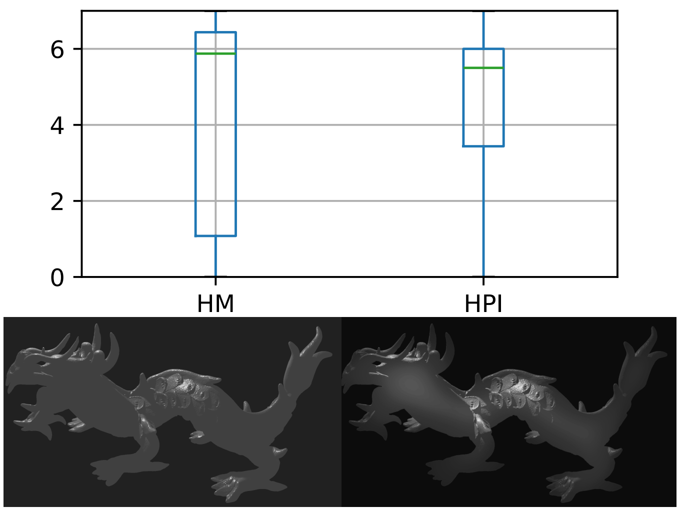


Fig. 8. Response to low-cost SSS dragons with black void background

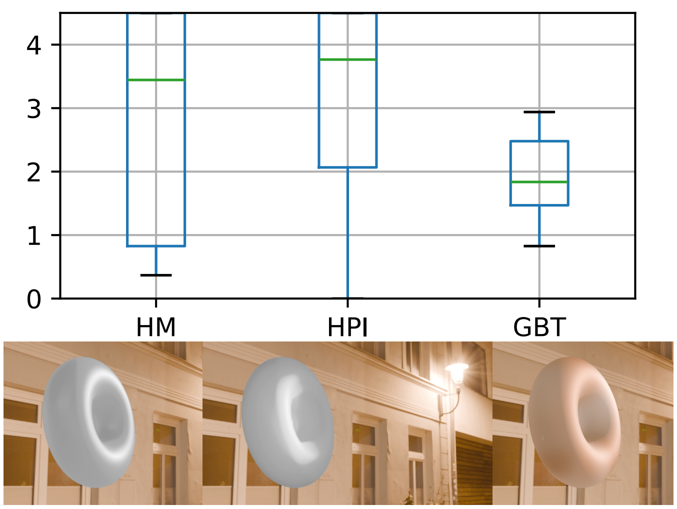


Fig. 9. Response to low-cost SSS toruses with image background

methods made the objects appear more translucent. Therefore, we are interested in seeing whether participants indicated whether the stimuli had significantly more SSS than $scale = 0$.

If a stimulus were perceptually wholly opaque, the probability distribution obtained in the matching experiment would have a mode at $scale = 0$ and it would be right-skewed, since it is not possible to choose a *scale* lower than 0. Therefore, we take the null hypothesis to be that the participants will choose scales in gamma distribution with shape $k = 1$ and, in lieu of a better alternative, we take the scale θ to equal the standard deviation of responses of the corresponding stimulus.

This number of participants does not allow us to assume the central limit theorem. We are therefore limited to nonparametric tests. Pearson's χ^2 test with a significance level set to $\frac{0.05}{18} = 0.0027$ using the Bonferroni correction gives that all 10 stimuli are perceived

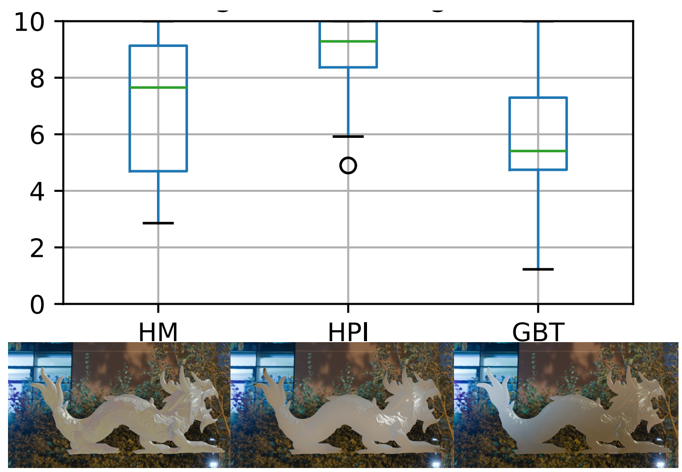


Fig. 10. Response to low-cost SSS Dragon with image background

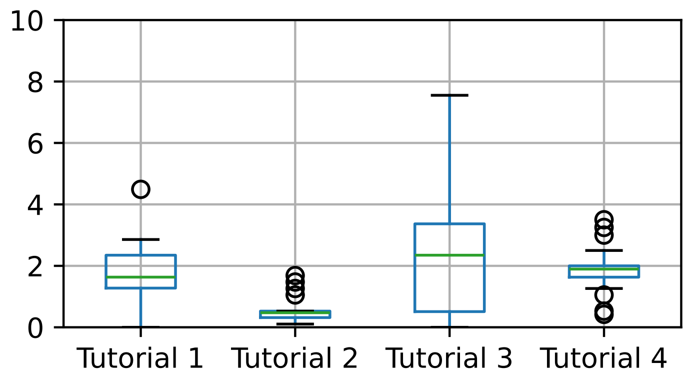


Fig. 11. Response to the introductory tutorial images

to have significantly more SSS than their opaque versions. The p-values can be found in Appendix A.

5 Discussion

In the following section, we discuss the results in detail.

5.1 Tutorial Images

Participants assigned the scale of the tutorial images with a much smaller IQR than the stimuli. The tutorial stimuli are rendered in the same way as the images in the test slider except that the objects are rotated. We hypothesise that these tutorial images are much closer in overall appearance to one of the test images than the low-cost methods. This makes the choice easier and less vague.

In the tutorial images, tutorial 3 has a much higher IQR and median scale than the rest even though it was rendered with *scale* $= 0$. This is because it was rendered with lighting from in-front as opposed to all the other objects which illuminated from behind. Participants likely overinflated its SSS because it is overall brighter than the other objects. This identical effect was noticed in previous work[Fleming and Bülthoff 2005]. This tendency for participants to try match the overall brightness instead of the amount of SSS in our view represents a limitation in the testing methodology.

5.2 High IQR

The statistical tests seem to show that the low-cost SSS methods made the opaque objects appear to have more SSS. However, there are some points of concern. As noted in Section 4.1, the IQR in the results is very high. In some cases, responses range over all allowed values. This puts the quality of the output images into question. Even though the images are perceived as containing more SSS, participants don't seem to agree on how much more. This is in contrast to the tutorial images that are rendered using expensive SSS techniques which all had a much lower variance than the perceptual approximations. Another contributing explanation for the high variance is that the image transformations perceptually modified other material properties that are not translucency. This resulted in stimuli whose apparent material type are not selectable for all dimensions of material type.

HM had an unacceptably high IQR in all cases so we suspect this to be the weakest method overall. HPI had a low IQR in the cases with the dragon, so we suspect it might be acceptable for uniform objects with high polygon counts. Finally, the GBT method had a low IQR for both objects, based on this we conclude it to be the most promising method. This comparison between IQRs is however not statistically rigorous and would require a scaling experiment to determine definitively.

5.3 Quality Difference between our Method and Fleming and Bülthoff [2005]

Fleming and Bülthoff [2005] presented the method we refer to as Histogram Matching and it seems to qualitatively work better in their research. This difference is explained by the fact that they used a rendered object that already had some SSS as the input image. This allows for the unilluminated side of the objects to be be non-uniformly shaded. Moreover, this non-uniform illumination allows the intensity curve to introduce shadows characteristic of translucent objects. In contrast, with an object rendered entirely opaquely, the unilluminated side of the object will necessarily have uniform intensity, making it impossible for a function based on intensity curves to produce convincing shadows.

We did not use some SSS as Fleming and Bülthoff [2005] did because rendering an object first with some SSS would negate the performance benefit we are aiming to achieve.

6 Limitations

All the presented low-cost approximation methods for SSS have parameters that will be manually chosen for each scene. Using these methods for translucent objects in real-time rendering applications like games would be infeasible if a good choice of parameters is highly dependent on scene description and difficult to find algorithmically.

Additionally, the presented methods only seem to be effective for uniform colourless translucent objects like the torus and dragon used in the experiment. Originally, we planned on using a head as a third model however we quickly realised that the methods would not convincingly reproduce SSS.

7 Conclusion

We find that it is possible to transform images of totally opaque objects into apparently translucent objects. Moreover, participants of a psychovisual experiment significantly identified these transformed images as containing more SSS. However, we question the quality of these images and believe more experiments are needed to qualify how well they work and in what situations they work best. The methods HPI and GBT have the most promise.

References

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Appendix A P-Values

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Tutorial 1: 0.05318866912320333
Tutorial 2: 0.9512792237499776
Tutorial 3: 0.20986408288802497
NLC Donut: 1.3453857080041447e-10
NLC Dragon: 1.7119326863118183e-10
Tutorial 4: 8.003634651536222e-07
HPCI Donut: 0.0010203301297000169
HPCI Dragon: 2.8443797883679094e-15
Background Donut: 3.2462067423581657e-12
Background Dragon: 1.267207872935753e-18
NLC Donut with background: 1.3361031386957241e-10
HPCI Donut with background: 3.007141868429583e-23
NLC Dragon with background: 6.464126682675302e-38
HPCI Dragon with background: 0.0
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