“The Dress” – Inferring Visual Perception Using Church

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Abstract

Our investigation assesses the way in which differing external illuminations can affect the visual perception of ambiguously illuminated photographs, and models this phenomenon using the programming language Church. Specifically, we assessed the way in which experimental participants saw “The Dress”, a known viral Internet image, under two different lighting conditions (sunlight and tungsten light). We modeled this phenomenon by inferring participants’ color perception of the dress using the illumination, reflectance, and luminance of the image under the different conditions. Our results mapped well to our collected data but we have concerns about our population sample.

Keywords: visual perception; the dress; Church; reflectance; illumination; luminance.

Background

In late February of this year, a photograph of a lace dress, designed by the fashion brand “Roman Originals” (see Figure 1), created a controversy that the Washington Post described as a “drama that divided a planet” (McCoy). A photograph of a dress was innocuously posted on Facebook by a couple who simply could not agree about its color, asking their friends for their opinions. The image made it’s way to Tumblr and soon became a Twitter sensation, generating over ten million anguished and confused tweets on the micro-blogging service. The two camps could not have been more stark: many saw the dress as blue and black, whilst the others saw it as white and gold. The authors themselves disagreed profusely about what they saw.

It soon became clear that a known phenomenon was at play. The reason the image was perceptually ambiguous soon emerged - but it is still unknown what visual processes are causing so many to see it one way and yet for others to be seeing it entirely differently.

A Visual Perception Primer

To understand what is happening with differing perceptions of the dress, it would be valuable to consider the processes involved in human visual perception. We are constantly engaging in causal inference when we see things. What our

Figure 1: Original photograph of “The Dress”.

eyes capture, the luminance of an object, is the product of its reflectance and its illumination. An essential human trait is the ability to discern how significant each factor is when we are seeing an object. The human ability to disentangle these two factors to decide on the actual color of an object is called color constancy (Plummer). This mechanism is valuable as it allows us not to be confounded by misplaced inferences of the relative importance of each input. Generally, we discern illumination by observing a multitude of objects and using an abundance of samples to select the relevant sources of illumination. We then causally infer the reflectance of an object.

Day to day, this mechanism works very well. We are able to accurately estimate the illumination and reflectance of individual objects because we have so many different objects of different luminance to sample from.

However, in the case of “The Dress”, we see only one object, in complete isolation, with ambiguous sources of illumination. The lack of reference points on the dress photo alters how we perceive its illumination, and leads to ambiguities (Rogers). Under certain perceived illumination profiles, the dress looks blue and black, and under other perceived illumination profiles, the dress looks white and gold. This changes the perceived reflectance of the dress in our minds.

So, the logic goes, if we subject the photograph to particular illumination profiles, we can expect different results in people’s recognition of the colors they see. We chose to investigate this phenomenon using sunlight, and tungsten, or “yellow” light. The wavelengths of these two illumination profiles vary enough such that we can expect the perceived luminance of the object to be different for different participants.

Related Work

There is a wealth of related work done by vision researchers that we are building on with our experiment. Edward Adelson’s “Checkerboard” illusion was the starting point for our inquiry (1993). His paper used a class of brightness illusions to demonstrate that our perception of brightness and reflectance is strongly affected by the object’s perceptual organization. This prompted us to begin assessing the factors that affected the color perception of “the dress”. Another paper we used as inspiration attempted to understand the perception of illusions by changing their colors, which gave us insight into the disparate computations involved in understanding illusions better (Anderson, Khang, & Kim, 2011). For a week or two, we were very interested in investigating whether anchoring the lightness values made a significant difference in the way the color of “The Dress” is perceived. We considered this line of inquiry because of research that demonstrated that the highest luminance of an object plays a disproportionately large role in establishing perceived lightness values in surrounding areas that are illuminated by the same source (Gilchrist et al., 1999). Eventually, we decided against that because of methodological difficulties in isolating and presenting particular parts of the image.

We are attempting to go beyond some of the research that has been done by incorporating distributions as opposed to just single dimensions – specifically, by assessing spectral distributions of reflectance.

Question

The question that we are investigating is *how can we build a model that simulates human interpretations of “The Dress’” color under varying illumination profiles?*

Methods

To answer our question, we first had to conduct an experiment using real world data with which to judge our model. It involved engaging participants to tell us what colors they saw when subjected to the image under particular illumination conditions.

Experimental Methods

For our first experiment, we set up two conditions in which participants viewed the image. The first condition entailed setting up a laptop, at full brightness and at a 100-degree angle, in broad daylight, facing the sun between the 10:30 am and 2:30 pm. The second condition involved setting up a laptop, at full brightness and at a 100-degree angle, inside a dark room with a tungsten lamp illuminating the screen (at a temperature of 3200K). On the screen, we presented the subject with a photo of the original dress, surrounded by a white background. For each condition, we had 30 participants stand two feet away from the screen, and we asked four questions: (1) what combination of colors did they see on the dress, (2) whether they had seen the dress before, (3) what colors they had seen the dress before and whether they could only see it in one way or the other, and (4) whether they suffered from any visual impairment (e.g. color-blindness, imperfect vision, etc.). The participants were either friends or strangers solicited around the area we conducted the experiment. To our and the participants’ knowledge, only one was color blind; many wore contacts or glasses; there was a mix of male and female participants, and they were between the ages of 18-35.

Results

Our results were rather modest, showing only a small discrepancy between the way the dress was observed in each condition. In the first condition, more participants saw white and gold than blue and black, as described in Table 1. In the second condition, both groups saw each color combination just as often, as documented in Table 2. Tables 6 and 7, in the appendix, contain all the raw participant data.

Table 1: Sunlight Condition

Colors Observed	Total
White and Gold	18
Blue and Black	12

Table 2: Tungsten Condition

Colors Observed	Total
White and Gold	15
Blue and Black	15

Modeling

Once we had collected our data, our next task was to construct a model that would accurately and correctly judge the likelihood an individual would see the dress one way or the other under particular illumination conditions. To do that, we use the programming language, Church. Before we could write out the model however, we needed to take measurements of the luminance of the dress as one of the key inputs of our model.

Photometer Readings

We used the photometer to measure the luminance and chrominance of different parts of the image. We did so by selecting six representative areas of the dress to measure, as detailed in Figure 2. We took measurements of each area three times, selecting the median result for our final reading.

Figure 2 shows the six locations (marked as x1, x2, x3, x4, x5 and x6) we took luminance readings. Table 3 shows our results. Yxy values are the measured luminance (Y) and the chrominance (xy). We transformed the numbers we found into RGB values and then into wavelengths as our measured luminance (Askarian). We average the final wavelength values for each color to get one representative luminance wavelength for each color in both conditions.

Figure 2: Measurement locations

Table 3: Photometer Results in Sunlight Condition

Dress Color	**Yxy**	**Converted RGB**	**Converted Wavelength**
Blue/White	155	171	439
	.292	190	
	.319	199	
Black/Gold	91	188	582
	.325	188	
	.350	172	

Table 4: Photometer Results in Tungsten Condition

Dress Color	**Yxy**	**Converted RGB**	**Converted Wavelength**
Blue/White	59.4	159	492
	.273	192	
	.301	213	
Black/Gold	35.9	198	590
	.356	187	
	.384	144	

Church Model

We started off creating one model, however following many complications, had to modify it for a second model. Both versions of the model had three key variables for modeling perception – illumination, reflectance, and luminance. The illumination profiles for both conditions were represented as multinomial distributions of wavelengths between 400 – 500 nm. After measuring the luminance of the dress with the photometer under both conditions, we decided this wavelength range was most important to our model and could give us the most accurate results. We did online research to find the illumination profiles for both conditions (Tungsten Halogen Lamps, Sunlight), and we calculated luminance by multiplying the reflectance and illumination profiles. Finally in our first model, we inferred the reflectance profile of the dress conditioned on the participant data we collected (Figure 5). However, our resulting reflectance profiles were inconclusive. We hypothesize that this occurred because the difference between our data sets was not very significant.

Next we modified our model to simulate human responses to the dress' color under different conditions, to which we then compared to the actual data we collected. Instead of inferring the reflectance of the image, we conditioned on the measured luminance (called 'observedLuminance' in our model) of the image being within a certain range of the inferred luminance, and inferred whether a participant would perceive the dress as blue/black or white/gold in the two conditions (Figure 6). Even though a small portion of our participants reported different color combinations than blue/black and white/gold, we only included these two choices because they were the most prominent responses. Furthermore, in our model we substituted observed luminance values for the blue/white strips of the dress, since these measured luminance values differed more than the black/gold strips under the different conditions.

Model Results

As mentioned in the previous section, we had to abandon the results from our first model, however the results from the second model nicely matched the data we collected. The model predicted that there is a roughly 50% chance that a participant observes the dress as blue/black in the Tungsten condition, and a roughly 40% chance the participant observes the dress as blue/black in the Sunlight condition.

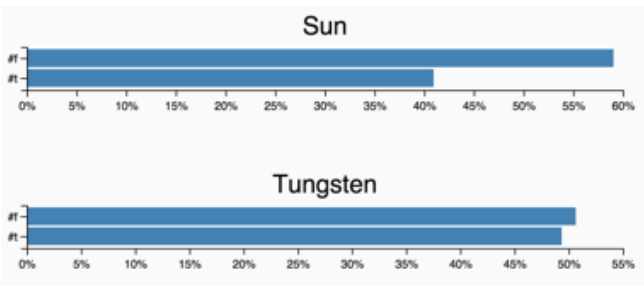

Figure 4: Church model results for both conditions.

Interpretations

We learned from our first and second models and participant responses that the illumination profiles we used may not have been different enough to result in significant differences between the two conditions. However, we were able to confirm that the population is widely divided on seeing the dress one way or the other, a notion supported by our model, our participant data, and the dress' notoriety online.

Conclusions

The results from our second model were promising and indicate that our model is accurately capturing the phenomenon we were interested in understanding.

But there are certainly changes we would have made, and many areas for improvement. What is perhaps most interesting in all of this is why exactly there is such a stark difference in the way different people see the dress in the first place – what is it about individuals' color constancy mechanisms that lead to such a massive discrepancy? What are the causes of the difference, and is there any way to predict how someone will see "The Dress" based on a variety of characteristics? This line of inquiry is more suited for more advanced vision scientists. For now, we must satisfy ourselves with considerations on how we could improve our own experiment.

First, we would endeavor to find people who have never seen "The Dress" to begin with. Out of the 60 people we had as participants, only two had not seen the image before. This matters, because we suspect that having seen the dress previously and consuming some of the commentary around the popular discrepancies and its true appearance may distort the way in which individuals perceive it later on.

A substantial plurality of our participants said that after seeing the dress one way, they could not "un-see" it. Effectively, they were wedded to one particular way of seeing the dress, which could have distorted our results – perhaps if they had seen the image in a particular condition for the first time, their perception of it could be different. This is an unknown that we would be well served to investigate more thoroughly.

Additionally, finding people who specifically could see it both ways may also be helpful in testing the robustness of our model, for analogous reasons as the above.

We also would prefer to have used participants who suffered from no visual impairments, because we do not know if that possibly introduces bias. Also, we would pay closer attention to differentiating factors in our subject population in case that helps us unlock any insights as to why people see it differently to begin with (gender has been proposed as one such factor). Finally, we would have also tried to engage younger people as subjects, because of their overall superior vision.

Acknowledgments

Thank you, Desmond Ong, for all the time you spent with us, fielding our queries and guiding us in the correct direction. Thanks, Professor Goodman and Michael Tessler, for your support over the course of the quarter, and a big thank you to Daniel Birman, who spared a great deal of his time to assist us with photometer calculations.

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Appendix

The appendix contains screenshots of both of our models (the original and final one), as well as the raw data from our experiment. Note that in the raw data tables, “Comment” describes the way in which the participant usually has seen the dress before, if they have seen it before.

Figure 6: Final Model.

```
(define wavelengths '(350 400 450 500 550 600 650 700 750))
(define illuminationSunProfile '(0 .4 .8 .95 1 .9 .87 .77 .8))
(define illuminationTungstenProfile '(.03 .1 .25 .36 .45 .6 .8 .85 .92))
(define illuminationSun (multinomial wavelengths illuminationSunProfile))
(define illuminationTungsten (multinomial wavelengths illuminationTungstenProfile))

(define samples
   (mh-query
    1000 10
    (define illuminationProfile illuminationTungstenProfile); can replace with illuminationTungsten
    (define reflectanceProfile (list (uniform 0 1) (uniform 0 1) (uniform 0 1) (uniform 0 1) (uniform 0 1)
                                (uniform 0 1) (uniform 0 1) (uniform 0 1) (uniform 0 1) ))
    (define luminanceProfile (map * reflectanceProfile illuminationProfile))
    (define (luminance) (multinomial wavelengths luminanceProfile)) ; its a wavelength value
    (define theta (uniform 350 750))
    (define observeBlack (> (luminance) theta))

    reflectanceProfile; inferring this

    (condition (equal? observeBlack #t)
               ;; ... remaining data points, 30 total
               (equal? observeBlack #t)) ; all tungsten data (15 #f), can be changed to
;; sunlight data (18 #f)
   ))
(scatter (map pair wavelengths (first samples)))
```

Figure 5: Initial Model.

```
(define wavelengths '(400 420 440 460 480 500))
(define illuminationSunProfile '(.41 .68 .75 .9 .95 .95))
(define illuminationTungstenProfile '(.1 .14 .24 .28 .32 .4))
(define illuminationSun (multinomial wavelengths illuminationSunProfile))
(define illuminationTungsten (multinomial wavelengths illuminationTungstenProfile))
(define observedLuminanceSun 439) ; based on photometer measurement
(define observedLuminanceTung 492) ; based on photometer measurement

(define (samples lightSource)
   (mh-query
    2000 10
    (define theta 465) ; halfway between observedLuminanceSun and observedLuminanceTung
    (define illuminationProfile (if (equal? lightSource 'sun) illuminationSunProfile
                                    illuminationTungstenProfile) )
    (define reflectanceProfile (list (uniform 0 1) (uniform 0 1) (uniform 0 1) (uniform 0 1) (uniform 0 1)
                                     (uniform 0 1)))
    (define luminanceProfile (map * reflectanceProfile illuminationProfile))
    (define (luminance) (multinomial wavelengths luminanceProfile)) ;its a wavelength value
    (define observedLuminance (if (equal? lightSource 'sun) observedLuminanceSun observedLuminanceTung))
    (define observeBlack (> (luminance) theta))

    observeBlack ; inferring what a participant would say (#t --> blue and black, #f --> white and gold)

    (flip (/ (- 100 (abs (- (luminance) observedLuminance))) 100))))

(hist (samples 'sun) "Sun")
(hist (samples 'tung) "Tungsten")
```

Table 6: Raw Data, Indoor Condition

Participant	Colors Observed	Seen Before?	Comment
1	Blue/Black	Yes	Mostly Black/Blue
2	White/Gold	Yes	Mostly White/Gold
3	White/Gold	Yes	Mostly White/Gold
4	White/Gold	Yes	Sees Both Ways
5	White/Gold	Yes	Mostly White/Gold
6	White/Gold	Yes	Only White/Gold
7	White/Gold	Yes	Only White/Gold
8	White/Gold	Yes	Only White/Gold
9	Blue/Gold	Yes	Sees Both Ways
10	Blue/Black	Yes	Only Blue/Black
11	White/Gold	Yes	Only White/Gold
12	Blue/Black	Yes	Mostly Blue/Black
13	White/Gold	Yes	Only White/Gold
14	Blue/Black	No	
15	Blue/Black	Yes	Mostly White/Gold
16	White/Gold	Yes	Mostly White/Gold
17	Blue/Black	Yes	Mostly Blue/Black
18	White/Gold	Yes	Only White/Gold
19	White/Gold	Yes	Only White/Gold
20	Blue/Black	Yes	Sees Both Ways
21	Blue/Black	Yes	Only Blue/Black
22	Blue/Black	Yes	Sees Both Ways
23	White/Gold	Yes	Only White/Gold
24	Blue/Black	Yes	Sees Both Ways
25	Blue/Black	Yes	Sees Both Ways
26	White/Gold	Yes	Only White/Gold
27	Blue/Gold	Yes	Sees Both Ways
28	White/Gold	Yes	Sees Both Ways
29	Blue/Black	Yes	Only Blue/Black
30	Blue/Black	Yes	Sees Both Ways

Table 7: Raw Data, Outdoor Condition

Participant	Colors Observed	Seen Before?	Comment
31	White/Gold	Yes	Mostly White/Gold
32	White/Gold	Yes	Mostly White/Gold
33	White/Gold	Yes	Mostly White/Gold
34	White/Black	Yes	Sees Both Ways
35	Blue/Black	Yes	Mostly Blue/Black
36	Blue/Black	Yes	Sees Both Ways
37	Blue/Black	Yes	Mostly Blue/Black
38	White/Gold	Yes	Mostly White/Gold
39	White/Gold	Yes	Mostly White/Gold
40	Blue/Black	Yes	Only Blue/Black
41	Blue/Black	Yes	Sees Both Ways
42	Blue/Black	Yes	Only Blue/Black
43	Blue/Black	Yes	Mostly Blue/Black
44	White/Gold	Yes	Mostly White/Gold
45	White/Gold	Yes	Only White/Gold
46	White/Gold	Yes	Mostly White/Gold
47	Blue/Black	Yes	Mostly Blue/Black
48	White/Black	Yes	Mostly Blue/Black
49	White/Gold	Yes	Only White/Gold
50	White/Gold	Yes	Only White/Gold
51	Blue/Black	Yes	Mostly Blue/Black
52	White/Gold	Yes	Only White/Gold
53	Blue/Black	No	
54	White/Gold	Yes	Only White/Gold
55	Blue/Black	Yes	Sees Both Ways
56	White/Gold	Yes	Sees Both Ways
57	White/Gold	Yes	n/a
58	White/Gold	Yes	Sees Both Ways
59	Blue/Black	Yes	Sees Both Ways
60	White/Gold	Yes	Only White/Gold