ETH zürich

Documentation of the teaching results from the spring semester 2016

Creative Data Mining

Matthias Standfest, Danielle Griego, and Gerhard Schmitt

iA Chair for Information Architecture

DARCH

DARCH

Chair of Information Architecture

Creative Data Mining

Documentation of teaching results

Matthias Standfest, Danielle Griego, and Gerhard Schmitt

Teaching
Matthias Standfest, Danielle Griego, and Gerhard Schmitt

Syllabi
http://www.ia.arch.ethz.ch/category/teaching/fs2016-creative-data-mining/

Seminar
Digital Urban Simulation

Students
Andrea Panzeri, Marco Jacomella, Ricardo Joss, Robert Schiemann, Yuequi Wang

Published by
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Department of Architecture
Chair of Information Architecture
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Cover picture:
Front side: Global Air and Sea Routes. https://c2.staticflickr.com/8/7792/17623764646_6104b2e99f_b.jpg

Course Description and Program

Creative Data Mining
Intuitively Analysing Design Ideas

The goal of this course is to introduce various data mining techniques for design and urban planning applications. Students will learn how to select relevant data sources and collect their own data using a “sensor backpack”. Various methods will be applied to a common project to evaluate the predominant influencing factors of the urban environment on our perceptual experiences. A select neighborhood in the city will be used as a case study. Final results will be presented in the last class.

The course will start with an initial overview to data mining and the relevant mathematics as well as an introduction to the programming tool (RStudio). Then students will learn how to use and interpret results from a machine-learning tool to cluster self-made design sketches, which automatically generate qualitative collages. Finally, students will collect data using a “sensor backpack” with environmental sensors such as noise, temperature, illuminance, and air particulates. Students will also generate the data for perceptual quality in this neighborhood through time-stamped and geo-referenced surveys and biofeedback wristbands. Students will be given a work-flow to collect, process, analyze and interpret this data which may be used in their final projects.

Where
HIT H 12

Supervision
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Information Science Lab
Wolfgang-Pauli-Strasse 27, 8093 Zurich
www.ia.arch.ethz.ch

22.02.2016	**Course Introduction** Introduce data-mining techniques and case study
29.02.2016	**Introduction to the Environment** Introduction to R Studio and clustering
07.03.2016	**From analog to digital analysis** Use hand-drawn sketched to auto-generated collages
14.03.2016	**Seminar week (No lecture)**
21.03.2016	**Analysis and interpretation I** Evaluate auto-generated collages
28.03.2016	**Holiday (No lecture)**
04.04.2016	**Time-series data analysis and Urban Planning** Introduction to time-series analysis
11.04.2016	**Data collection with sensor backpack** Collect data and introduce workflows
18.04.2016	**Holiday (No lecture)**
25.04.2016	**Analysis and interpretation II** Evaluate sensor backpack data
02.05.2016	**Q&A Feedback Workshop** Finalise semester projects
09.05.2016	**Final iA critique** Combined critique with the other iA courses (14:00 - 16:00)

Requirement: Former knowledge of any digital tool or coding language is most welcome but NOT required. You only need to provide a reasonable amount of motivation and of course a notebook.

* Total 60 h = 2 ECTS

Exercises 40% (documentations)
Final Presentation 40% (Final project)
Attendance 20%

The most recent outline will be found on www.ia.arch.ethz.ch

Chair for
Information
Architecture

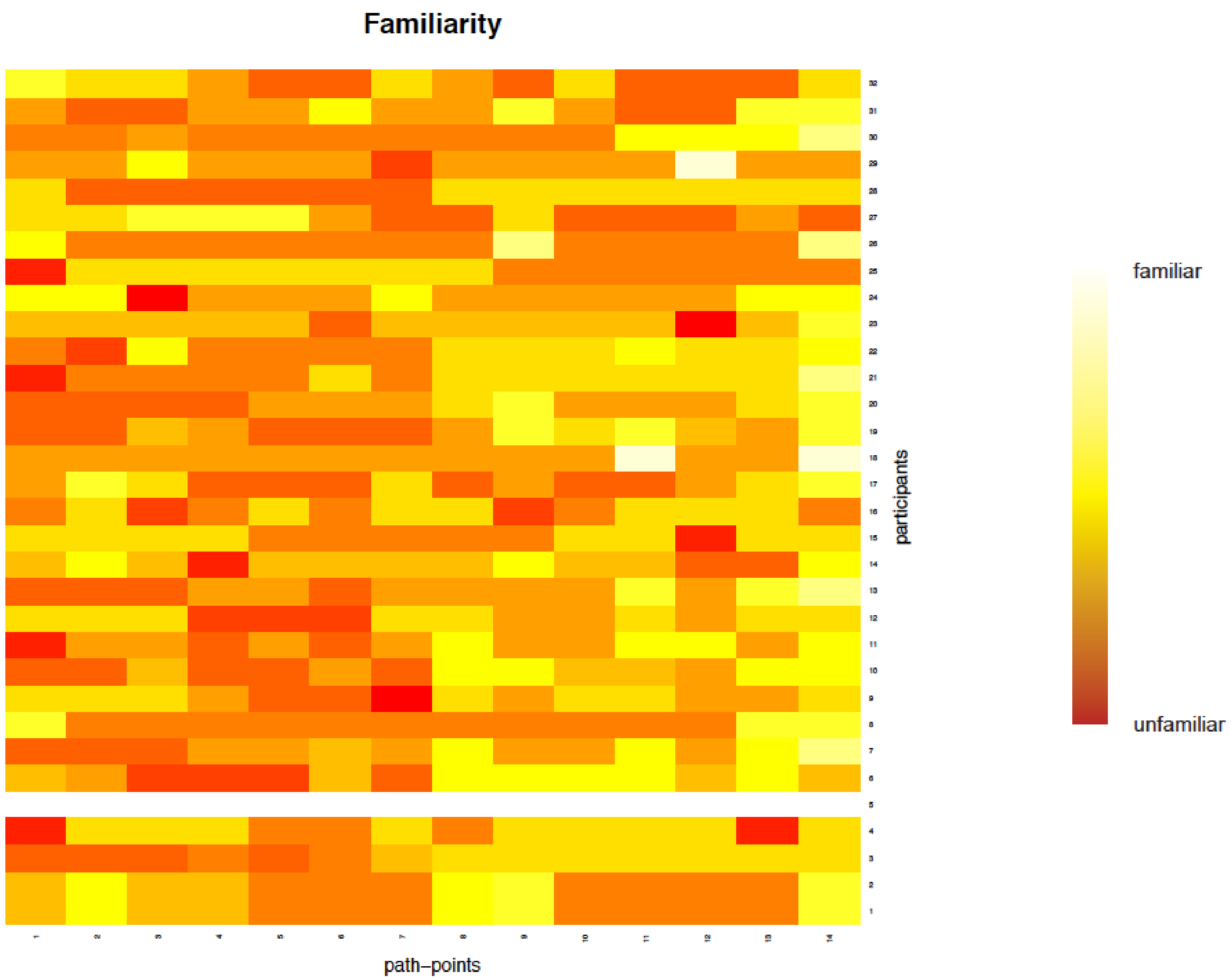
Content

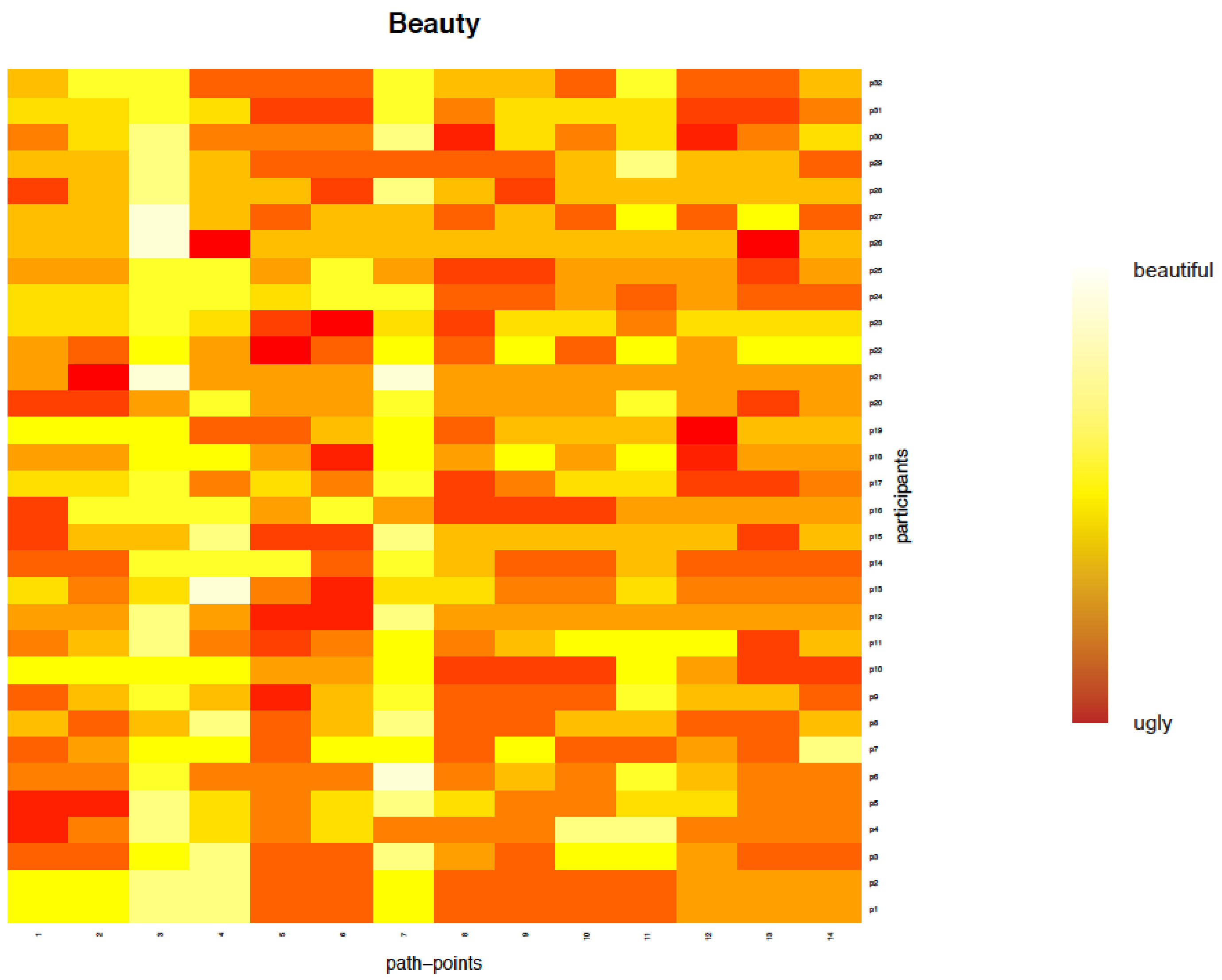
Objectivity, Subjectivity, Colour

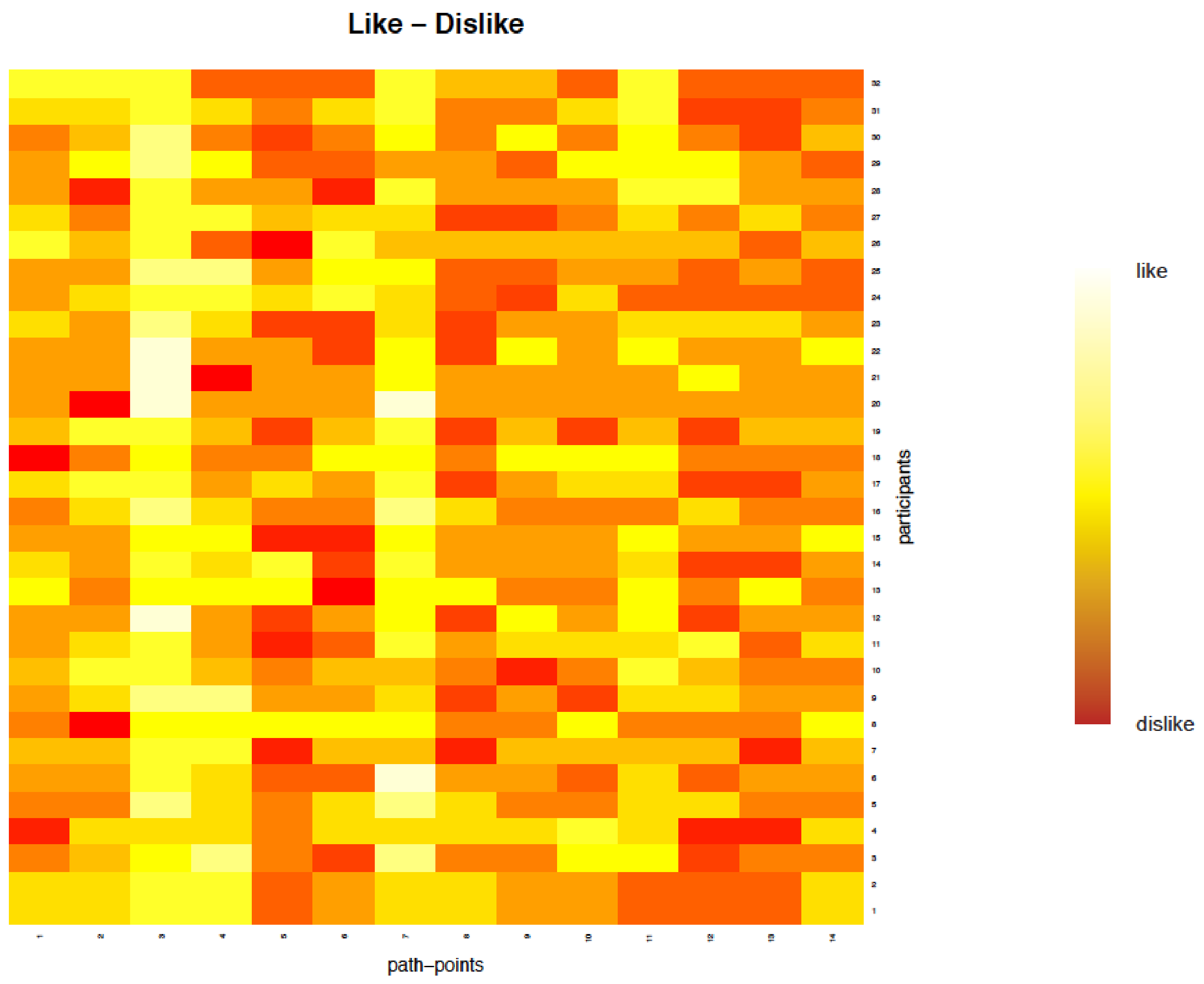
Student: Andrea Panzeri

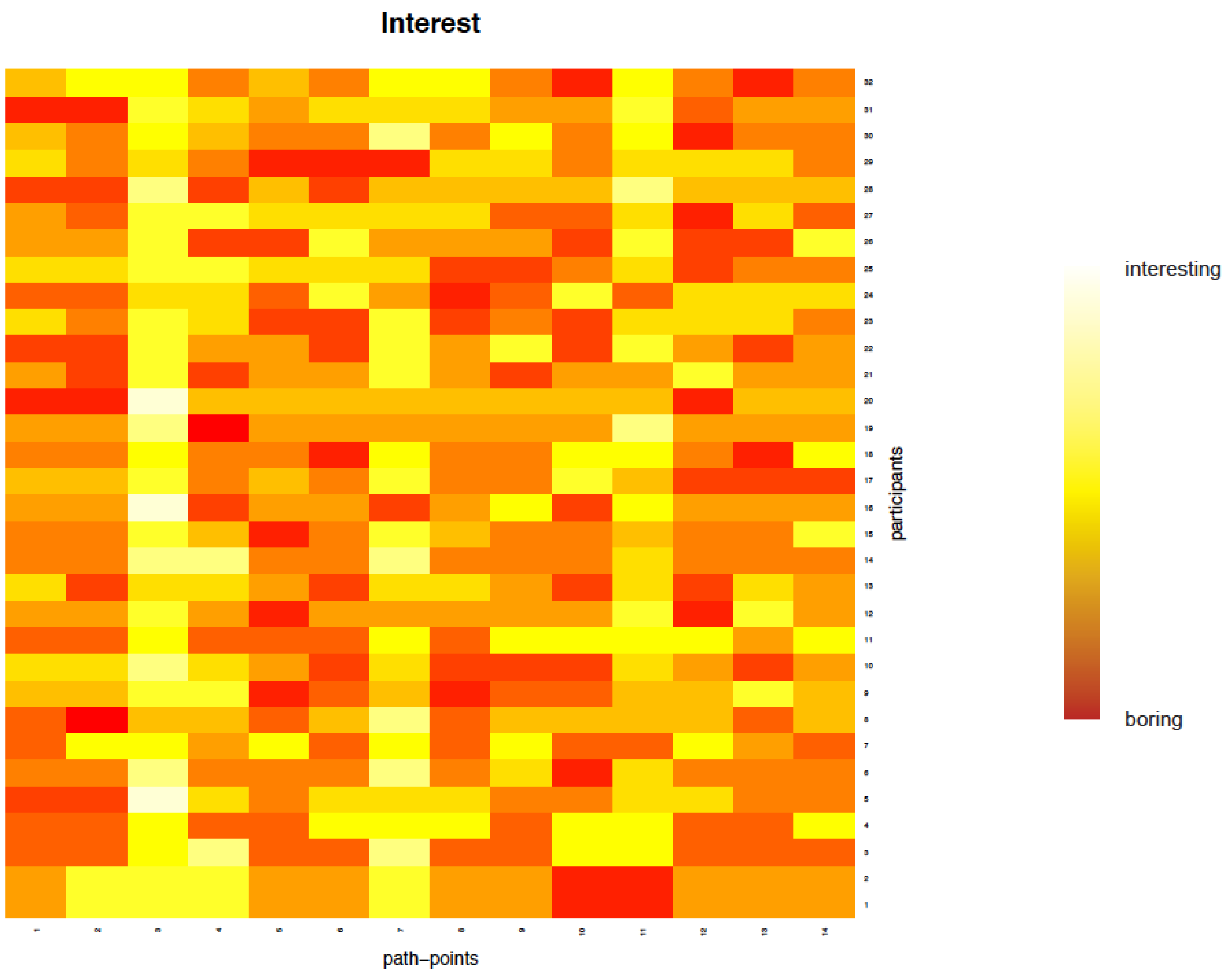
Thesis Question

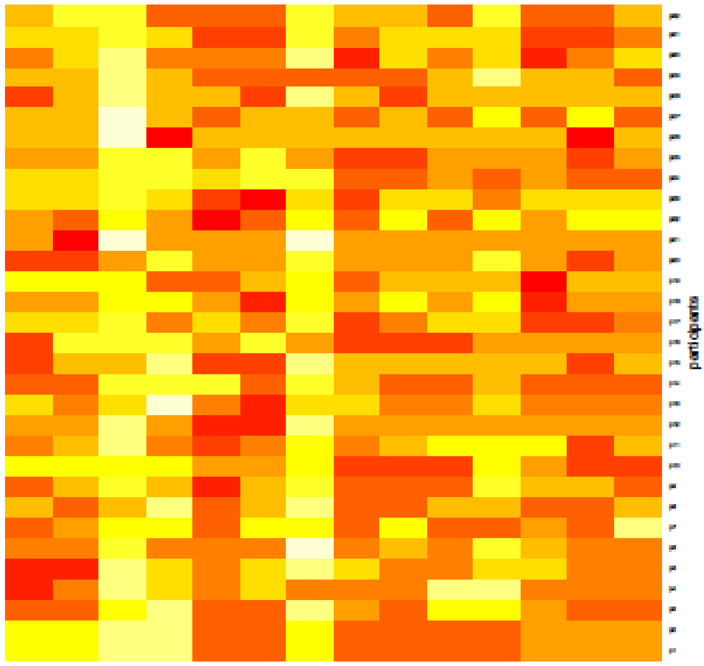
How can I analyze and judge objective and subjective data? How do they influence each other?
Is the color (or the absence of it) influencing our perception of the the urban environment?



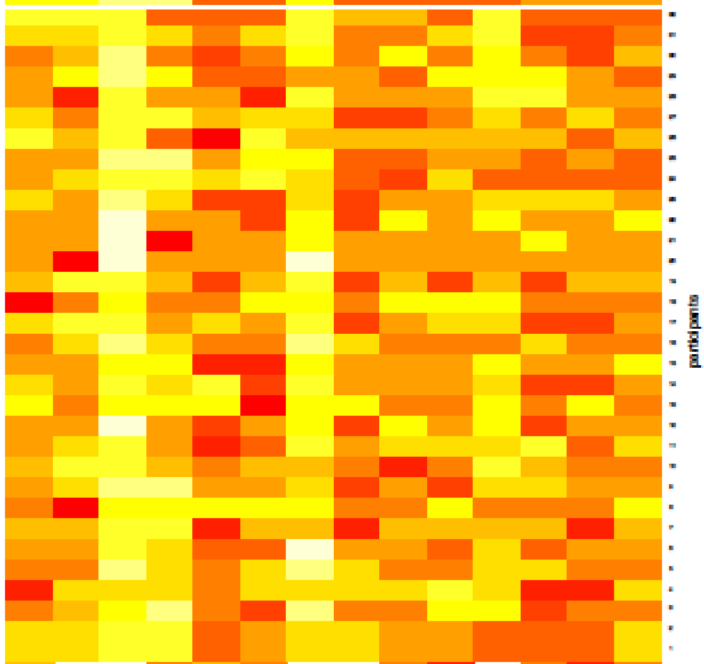

Beauty
participants
path–points
beautiful
ugly


Like – Dislike
participants
path–points
like
dislike

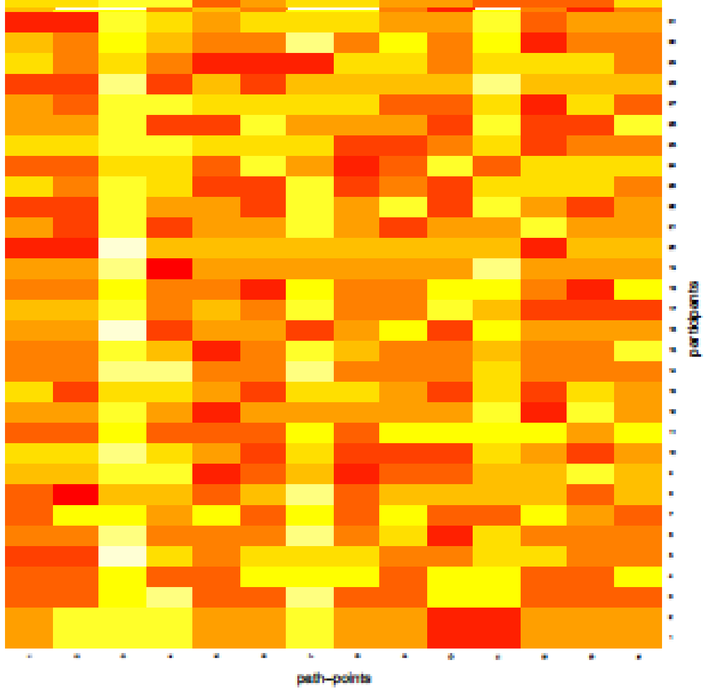

Interest
participants
path–points
interesting
boring



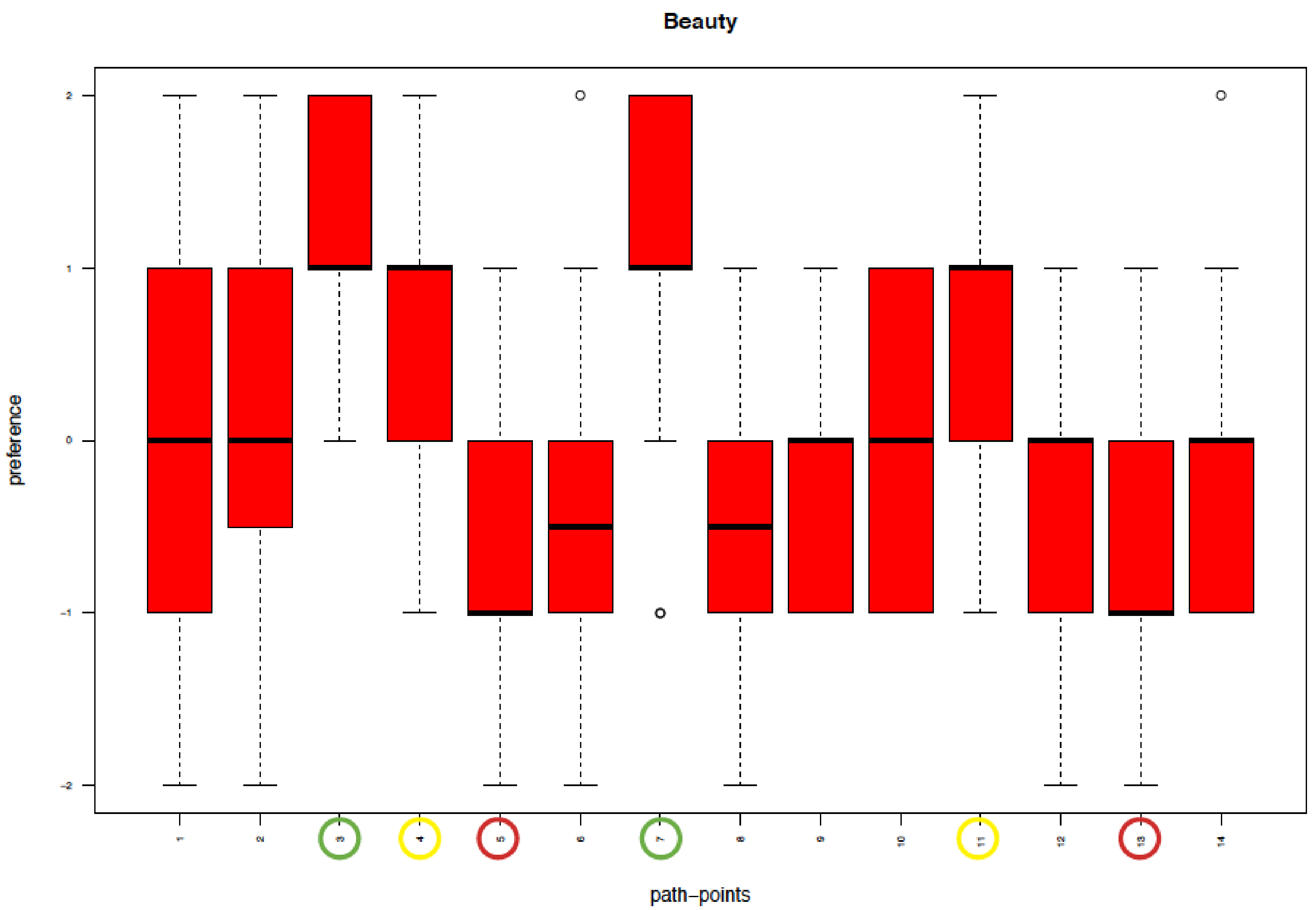
Beautiful - Ugly



Like - Dislike



Interesting - Boring


Beauty
preference
path–points
2
1
0
-1
-2
1
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4
5
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7
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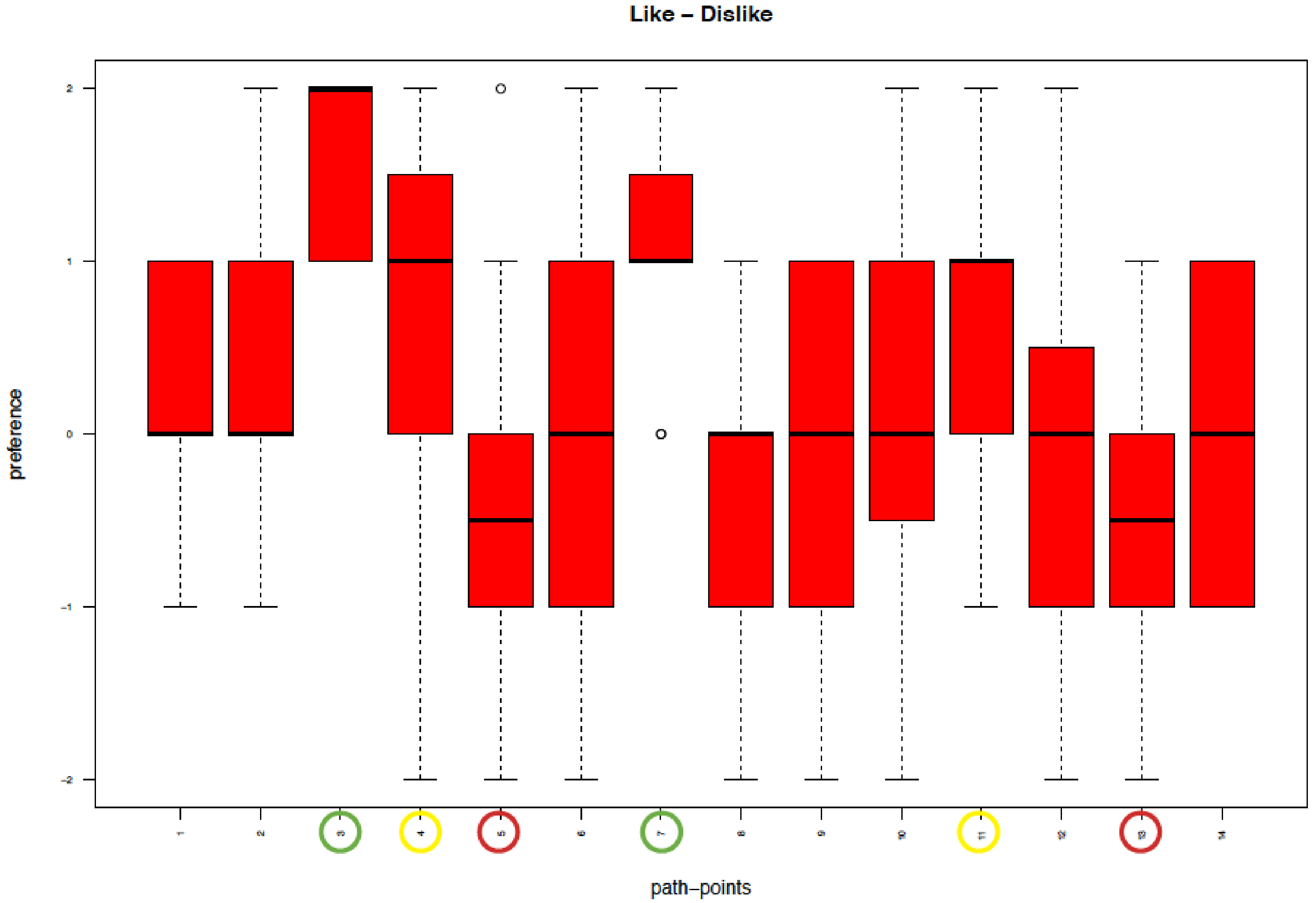
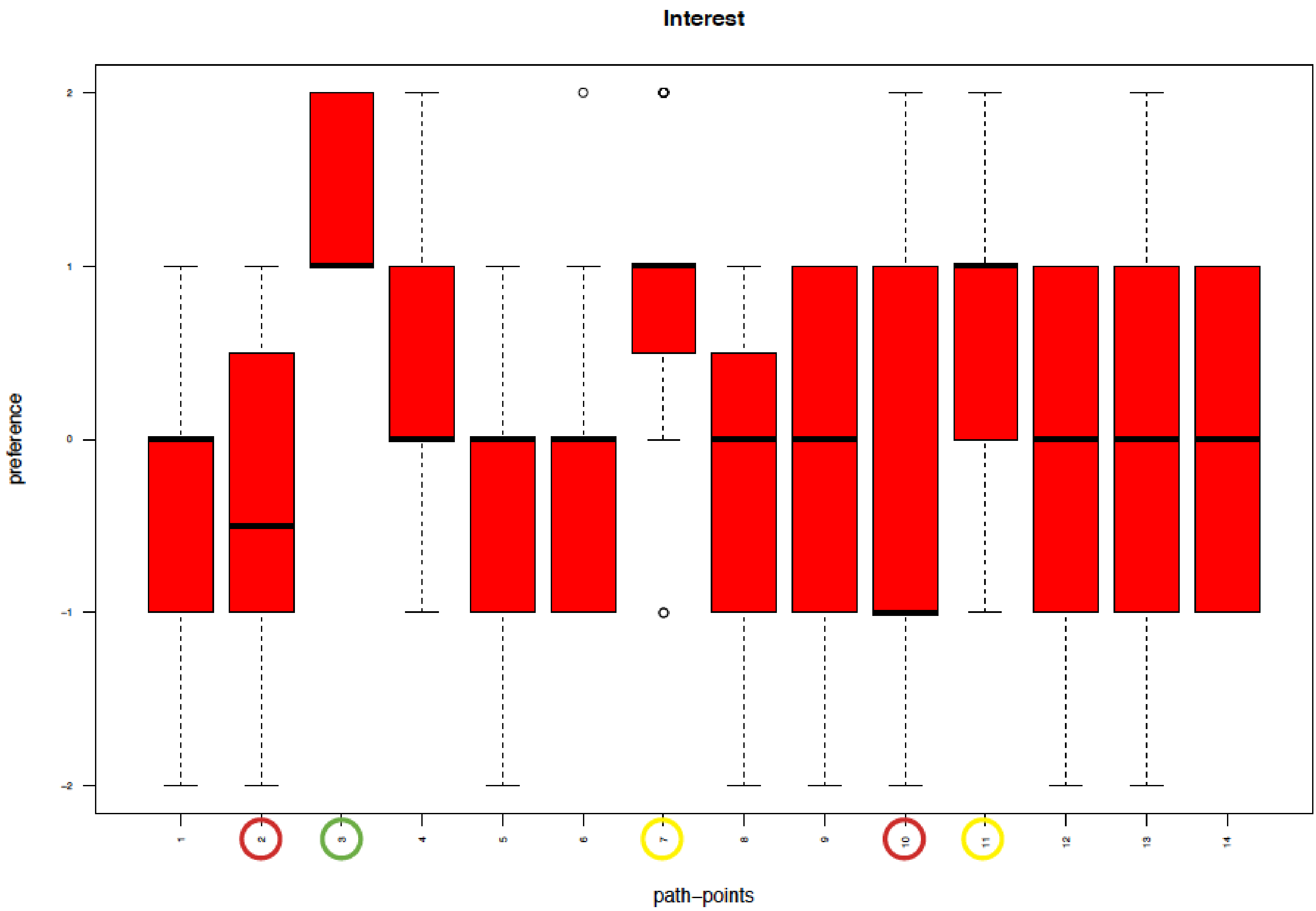
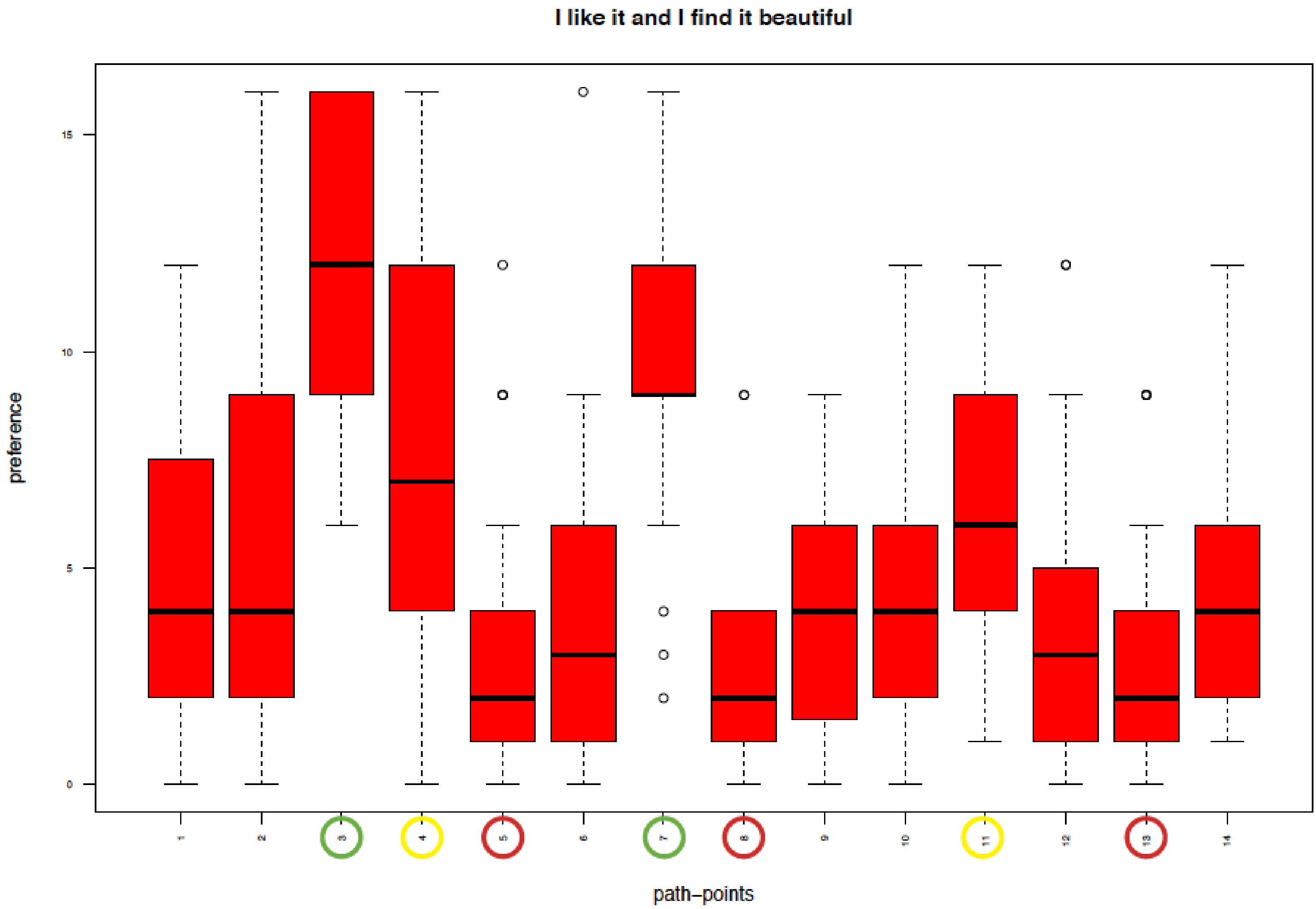
12
13
14

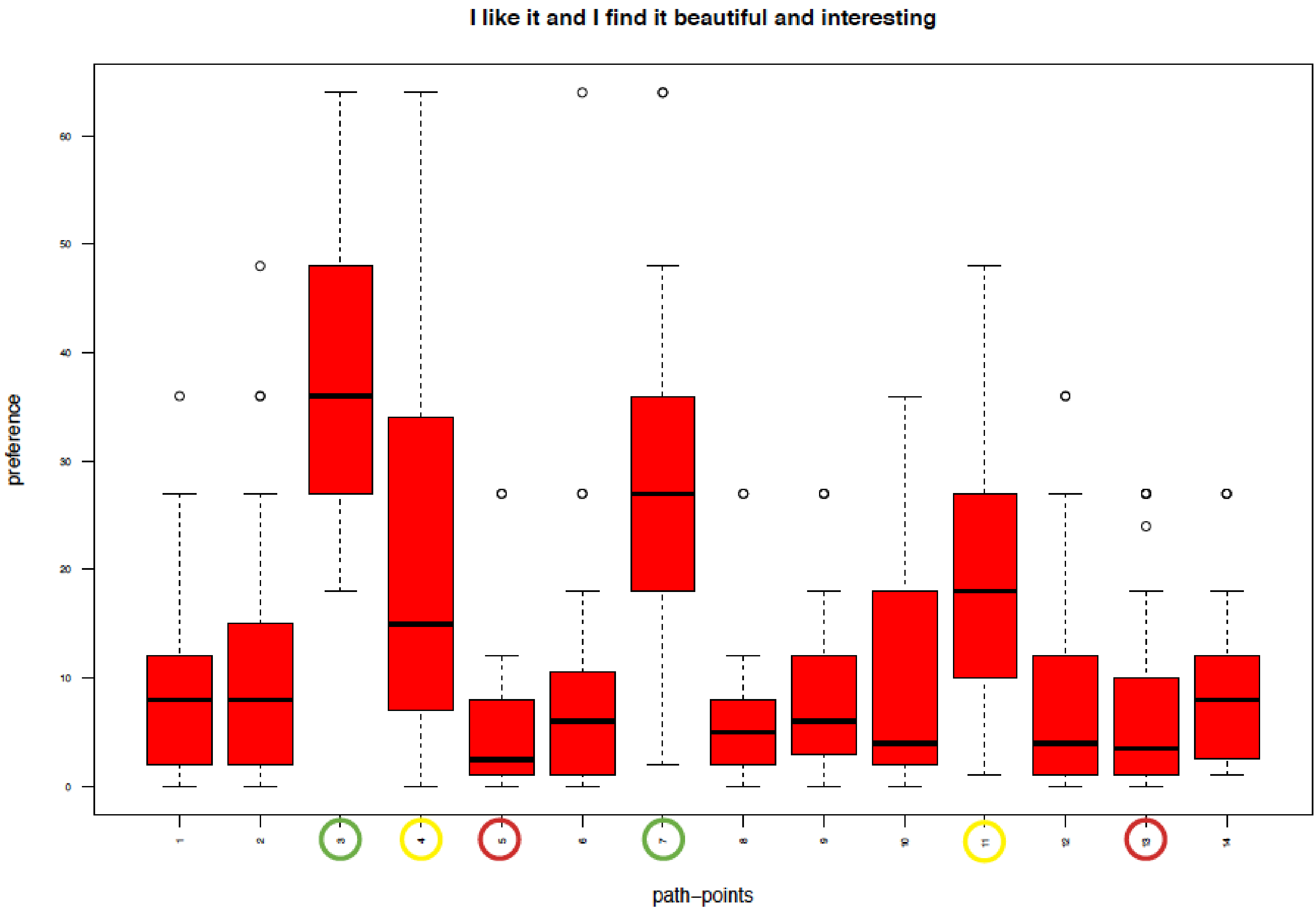


Like – Dislike
preference
2
1
0
-1
-2
path–points


Interest
preference
2
1
0
-1
-2
1
2
3
4
5
6
7
8
9
10
11
12
13
14
path–points



I like it and I find it beautiful
preference
path–points
15
10
5
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14


I like it and I find it beautiful and interesting
preference
path–points
0
10
20
30
40
50
60
1
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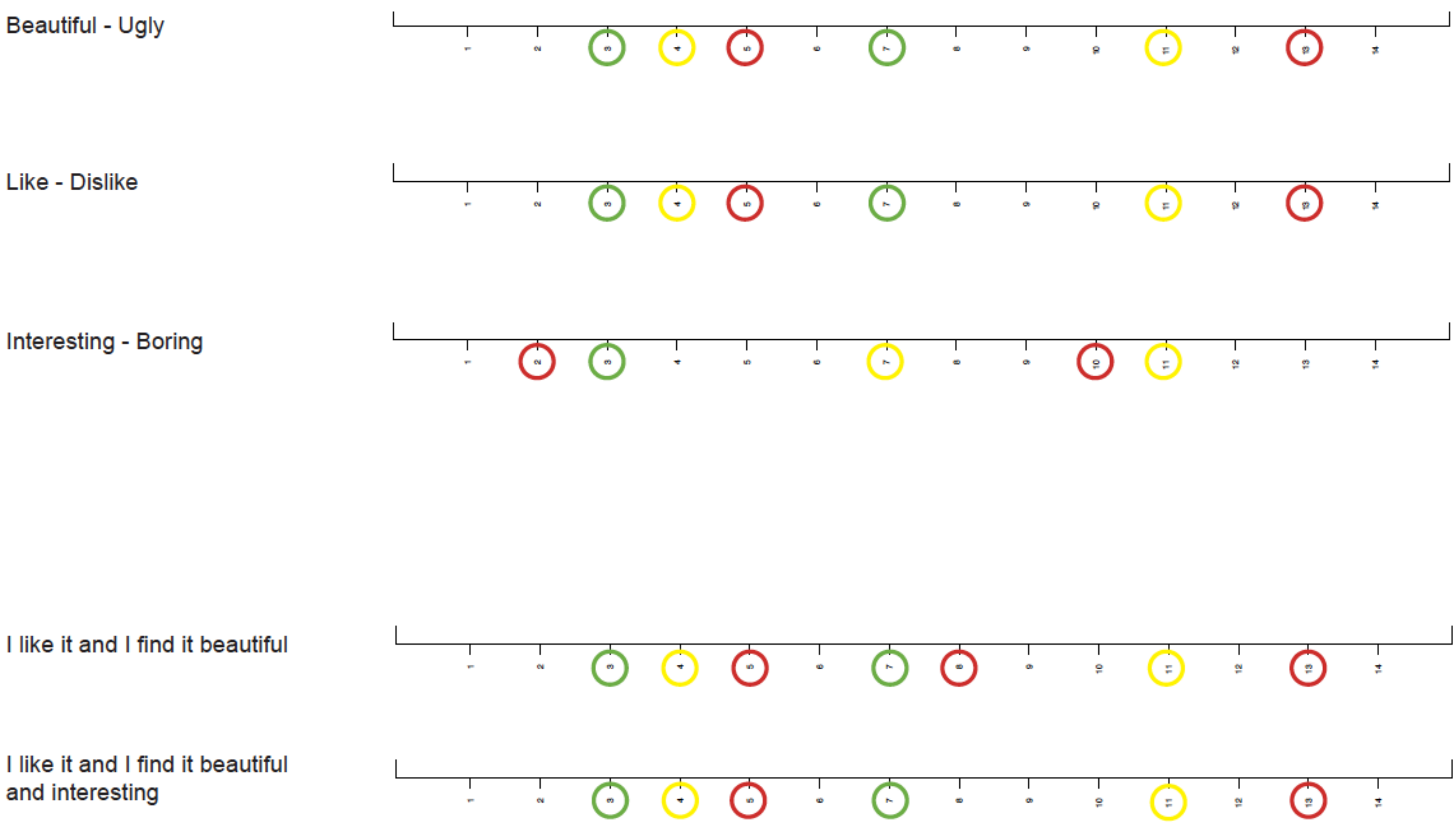
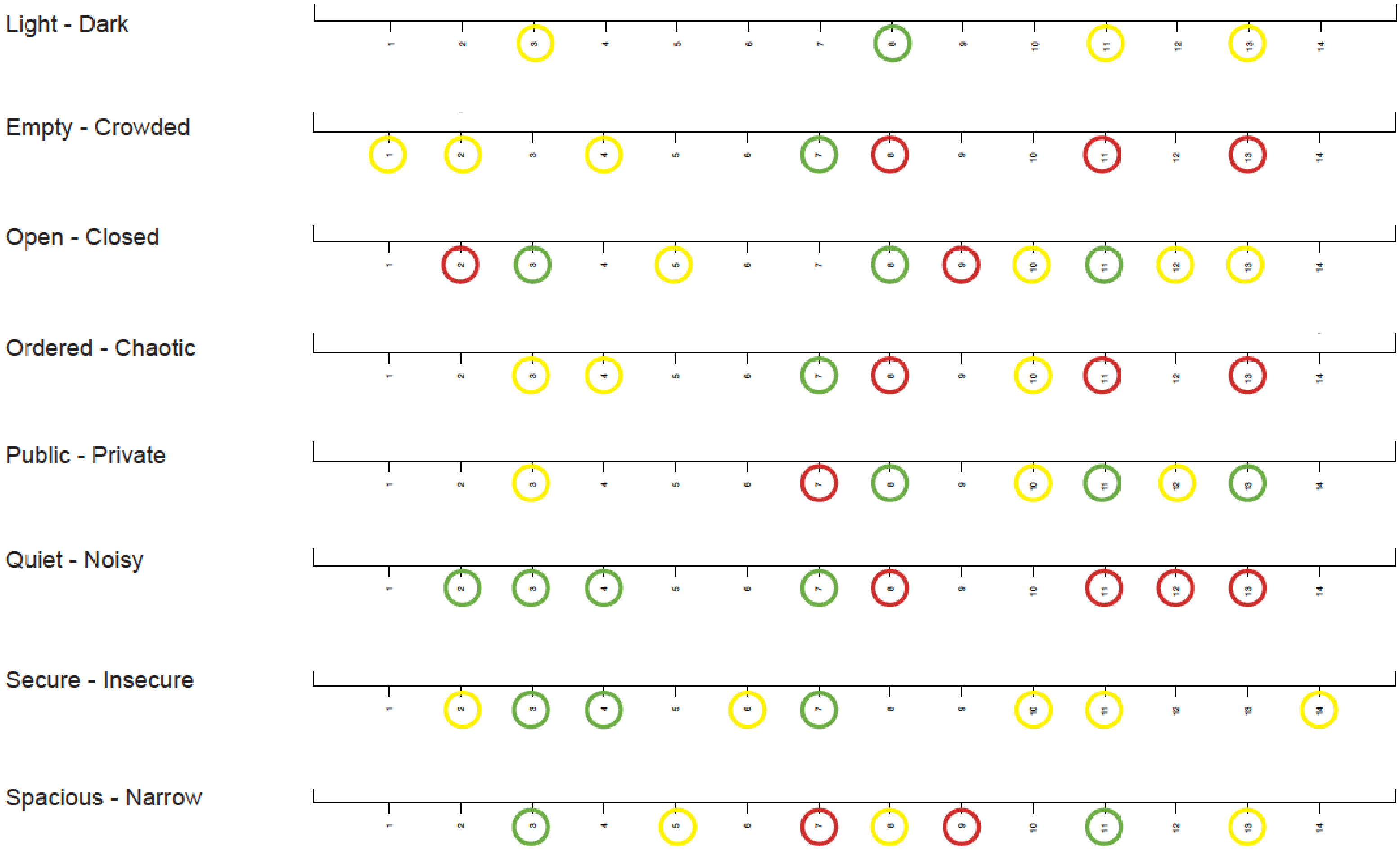
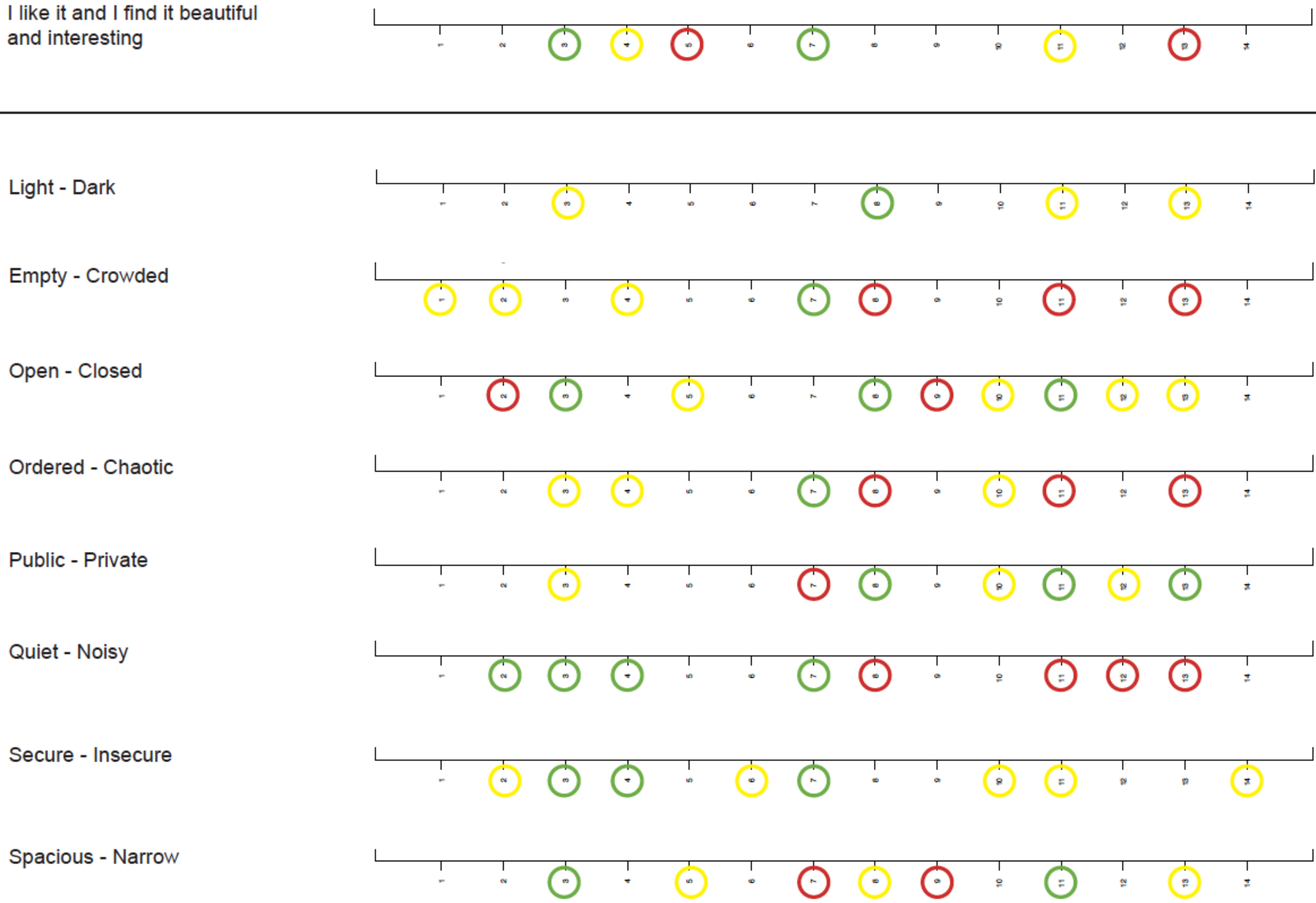
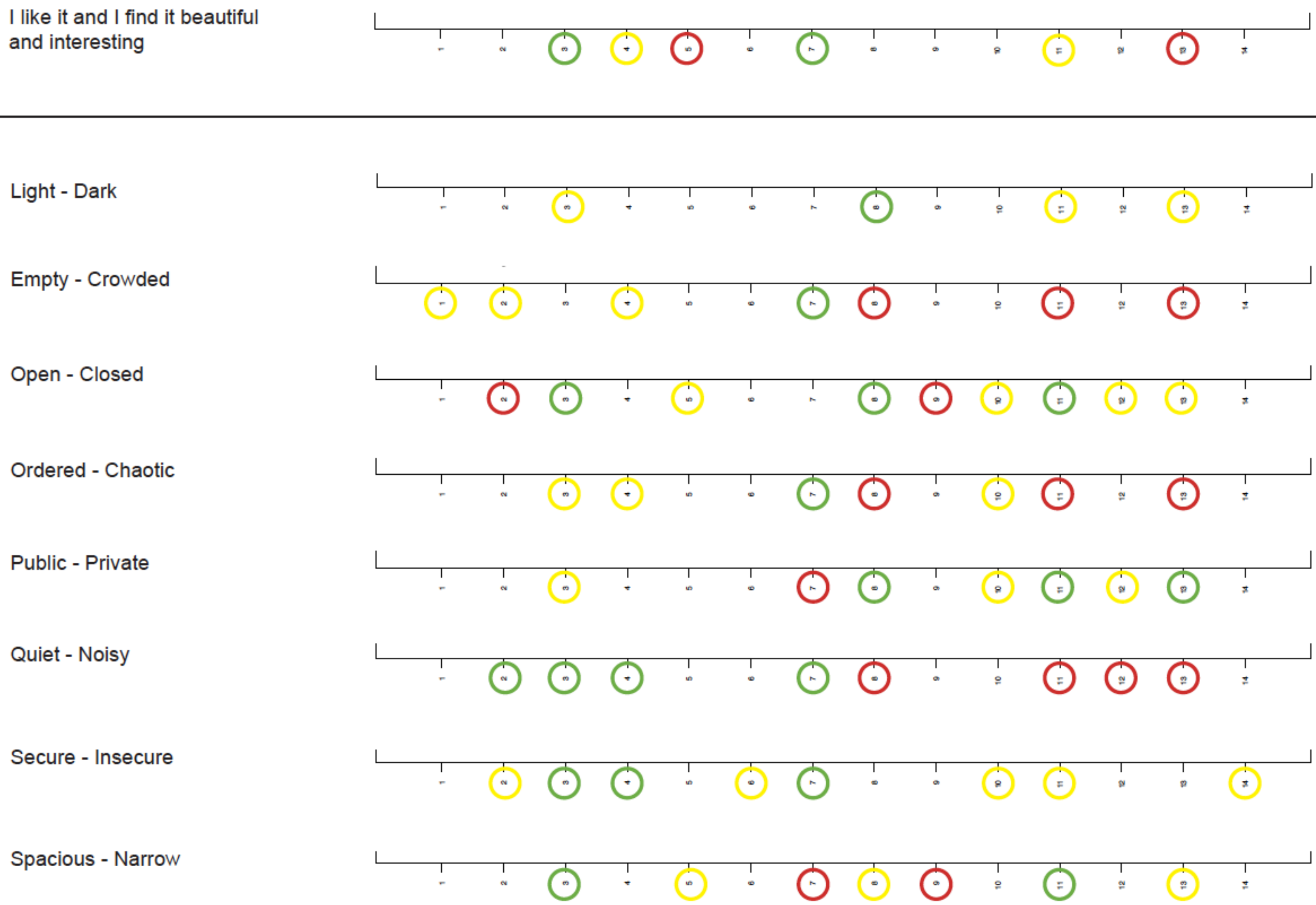
6
7
8
9
10
11
12
13
14


Beautiful - Ugly
Like - Dislike
Interesting - Boring
I like it and I find it beautiful
I like it and I find it beautiful and interesting


Light - Dark
Empty - Crowded
Open - Closed
Ordered - Chaotic
Public - Private
Quiet - Noisy
Secure - Insecure
Spacious - Narrow


I like it and I find it beautiful
and interesting
Light - Dark
Empty - Crowded
Open - Closed
Ordered - Chaotic
Public - Private
Quiet - Noisy
Secure - Insecure
Spacious - Narrow


I like it and I find it beautiful and interesting
Light - Dark
Empty - Crowded
Open - Closed
Ordered - Chaotic
Public - Private
Quiet - Noisy
Secure - Insecure
Spacious - Narrow

I like it and I find it beautiful
and interesting

Light - Dark

Empty - Crowded

Open - Closed

Ordered - Chaotic

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I like it and I find it beautiful and interesting

Light - Dark

Empty - Crowded

Open - Closed

Ordered - Chaotic

Public - Private

Quiet - Noisy

Secure - Insecure

Spacious - Narrow

I like it and I find it beautiful and interesting

5

Light - Dark

5

Empty - Crowded

5

Open - Closed

5

Ordered - Chaotic

5

Public - Private

5

Quiet - Noisy

5

Secure - Insecure

5

Spacious - Narrow

5

Conclusion

The objectivity of subjectivity (when what is personal becomes universal).The relativity of objectivity (sometimes we like opposite qualities in different places).No more white buildings! (or maybe we just like warm colors).

Data are more human than what I thought.

City is only Noise

Student: Marco Jacomella

“Noise has various health, economic and social effects,
the occurrence and intensity of which increase as the sound level rises.”

- Noise pollution in Switzerland,
Federal Office for the Environment FOEN Bern, 2009

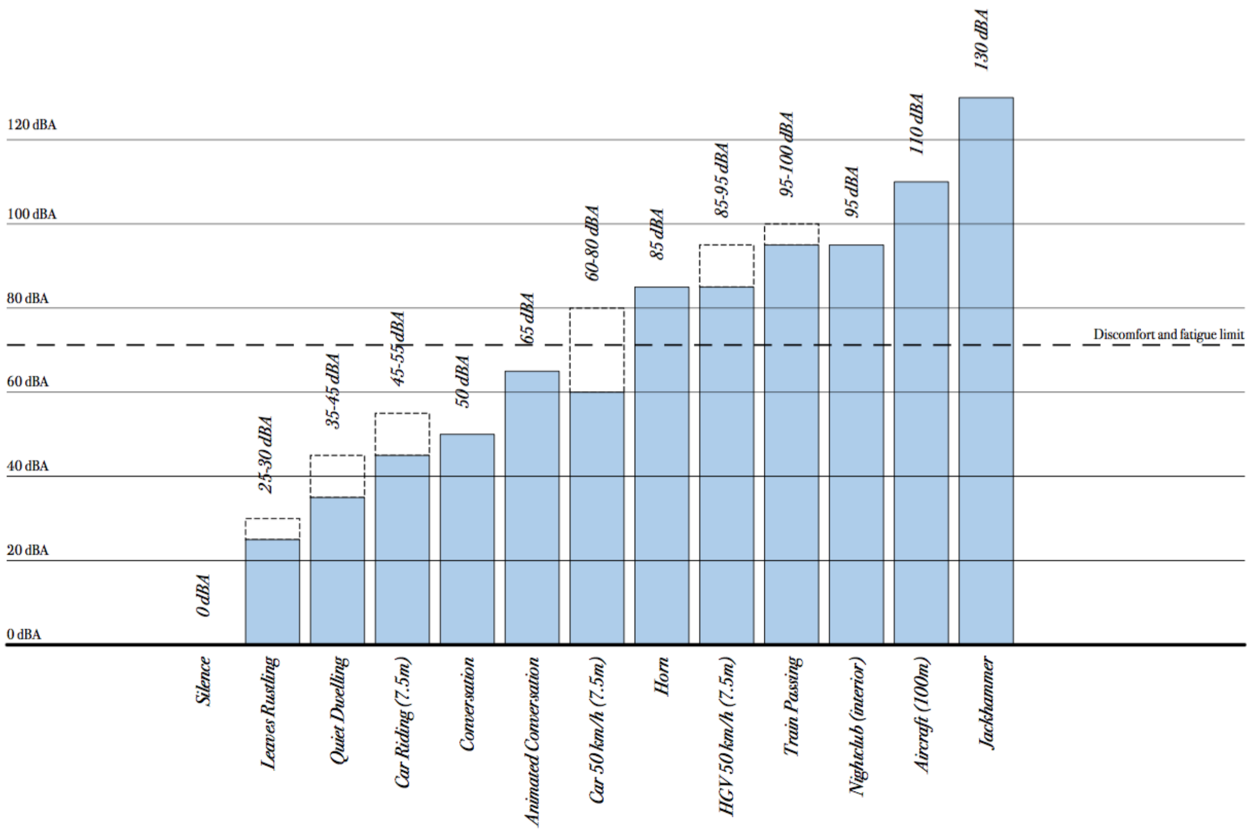
Questions

Which effect has noise on spatial perception?

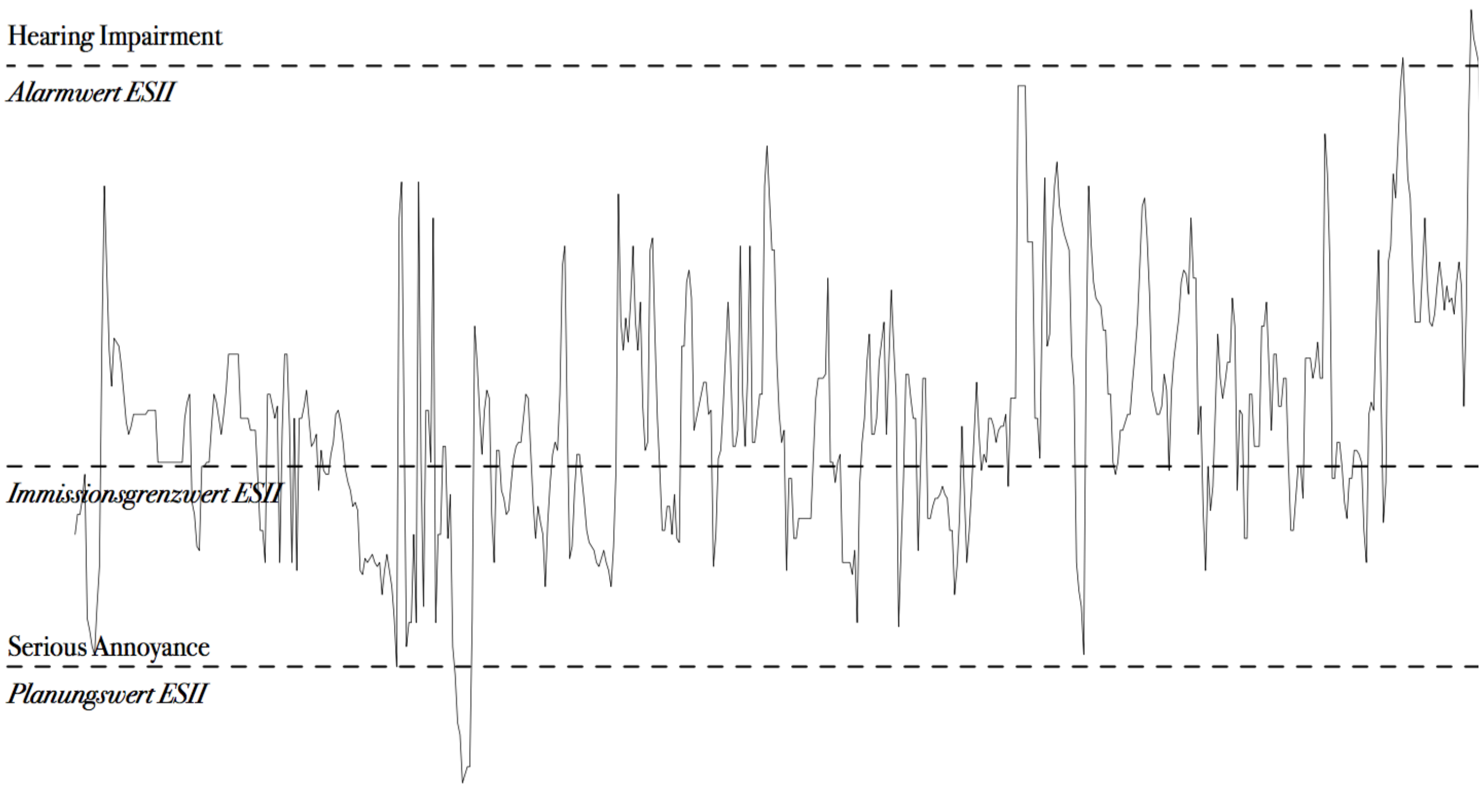
How much noise inflfluence personal perception?

How does noise impact the liveablity of a city?

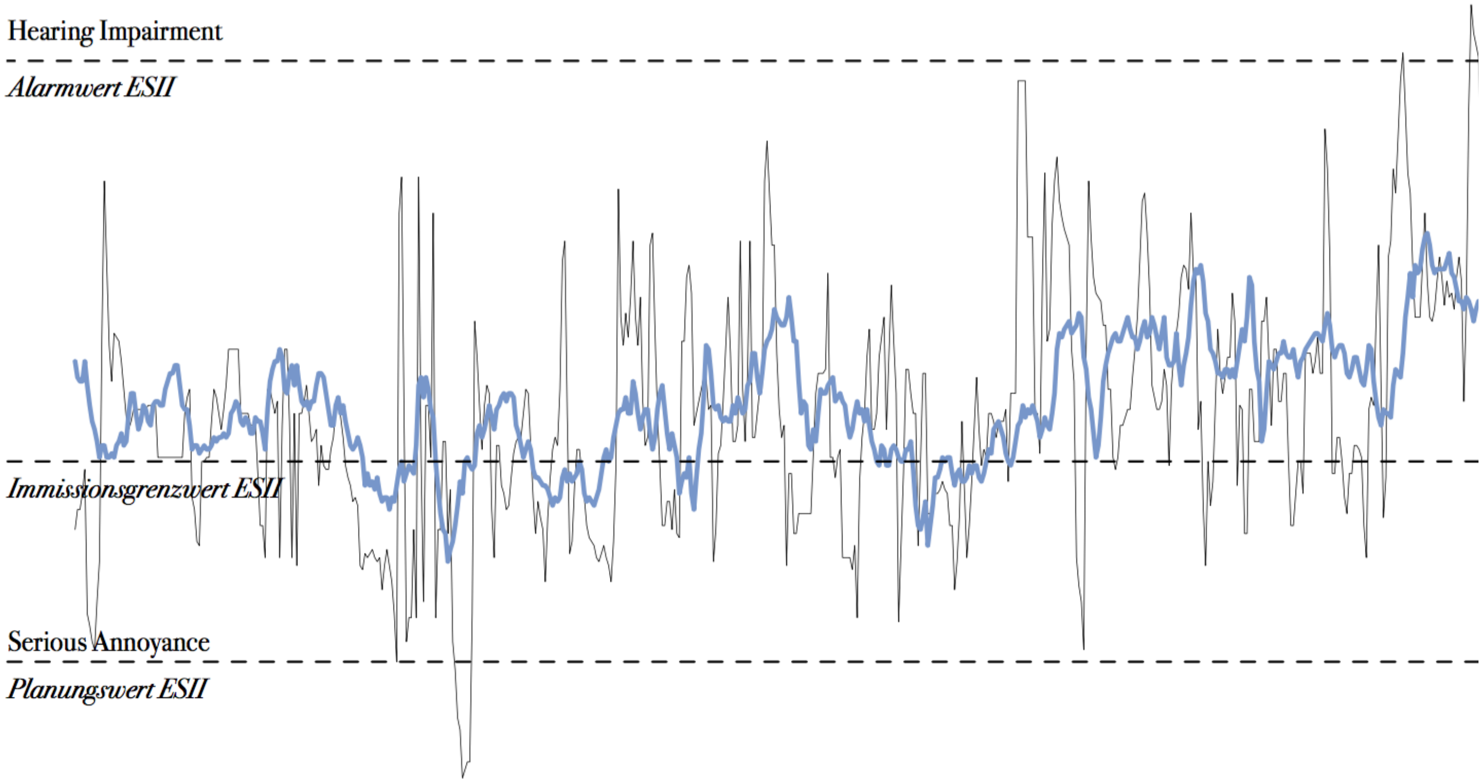
What is noise?



Survey 21st April, 2/3 P.M.



25 Surveys. Average



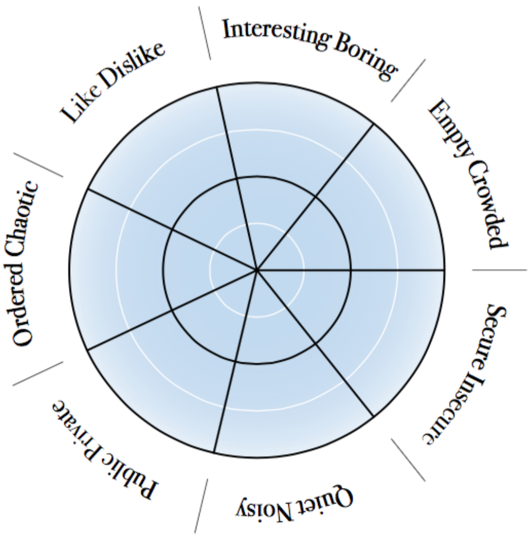
A subjective reading

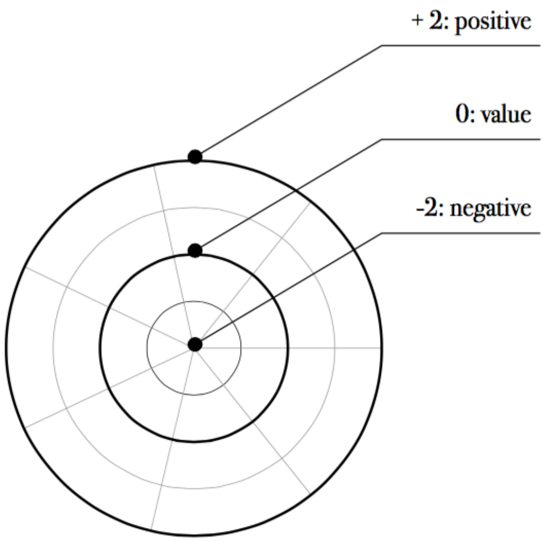
Beautiful	Ugly
Empty	Crowded
Familiar	Unfamiliar
Interesting	Boring
Light	Dark
Like	Dislike
Open	Enclosed
Ordered	Chaotic
Public	Private
Quiet	Noisy
Secure	Insecure
Spacious	Narrow

A subjective reading related to noise

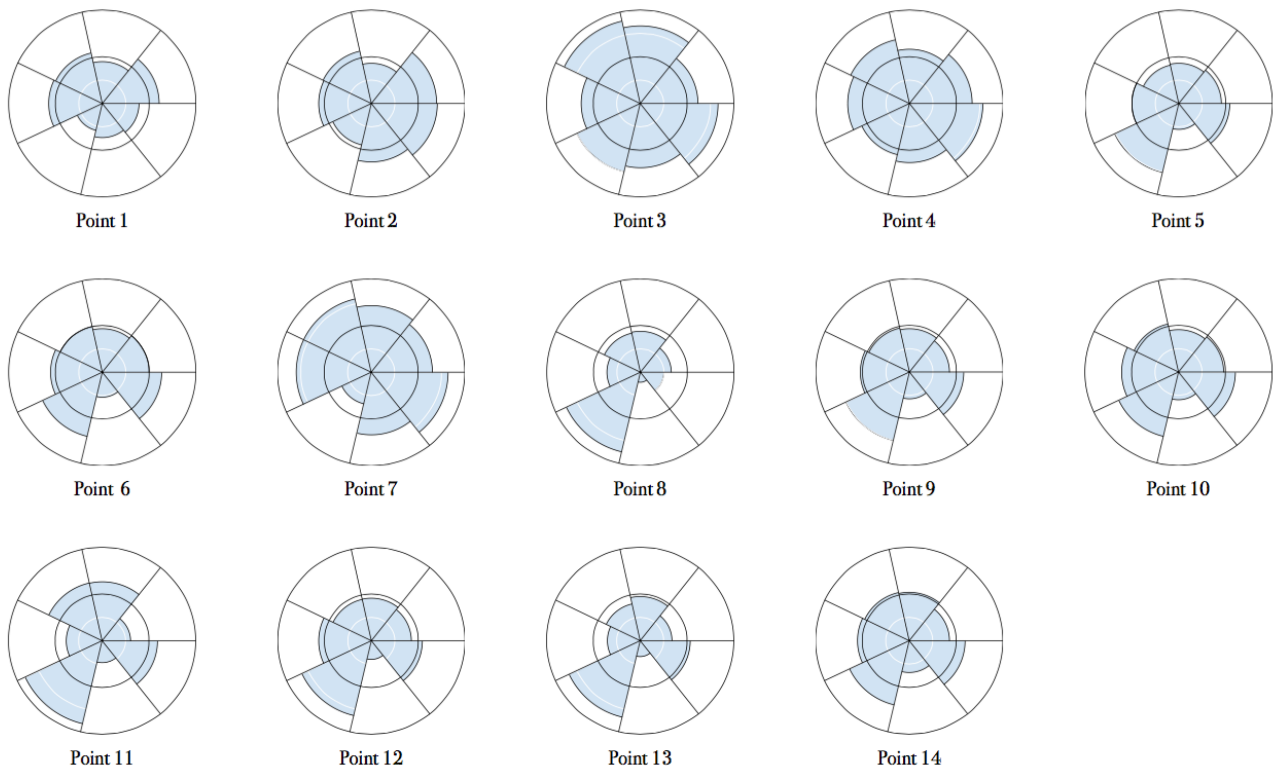
Beautiful	Ugly
Empty	Crowded
Familiar	Unfamiliar
Interesting	Boring
Light	Dark
Like	Dislike
Open	Enclosed
Ordered	Chaotic
Public	Private
Quiet	Noisy
Secure	Insecure
Spacious	Narrow

Data interpretation: radar chart

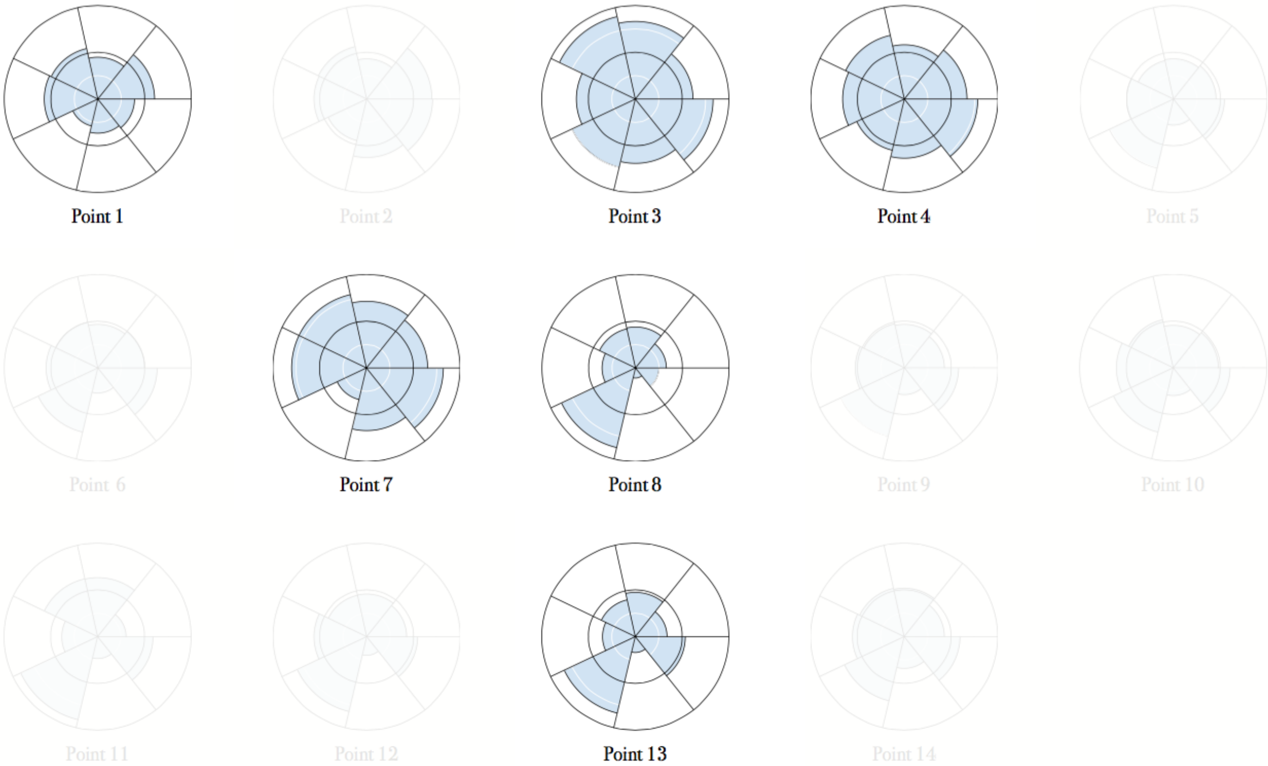


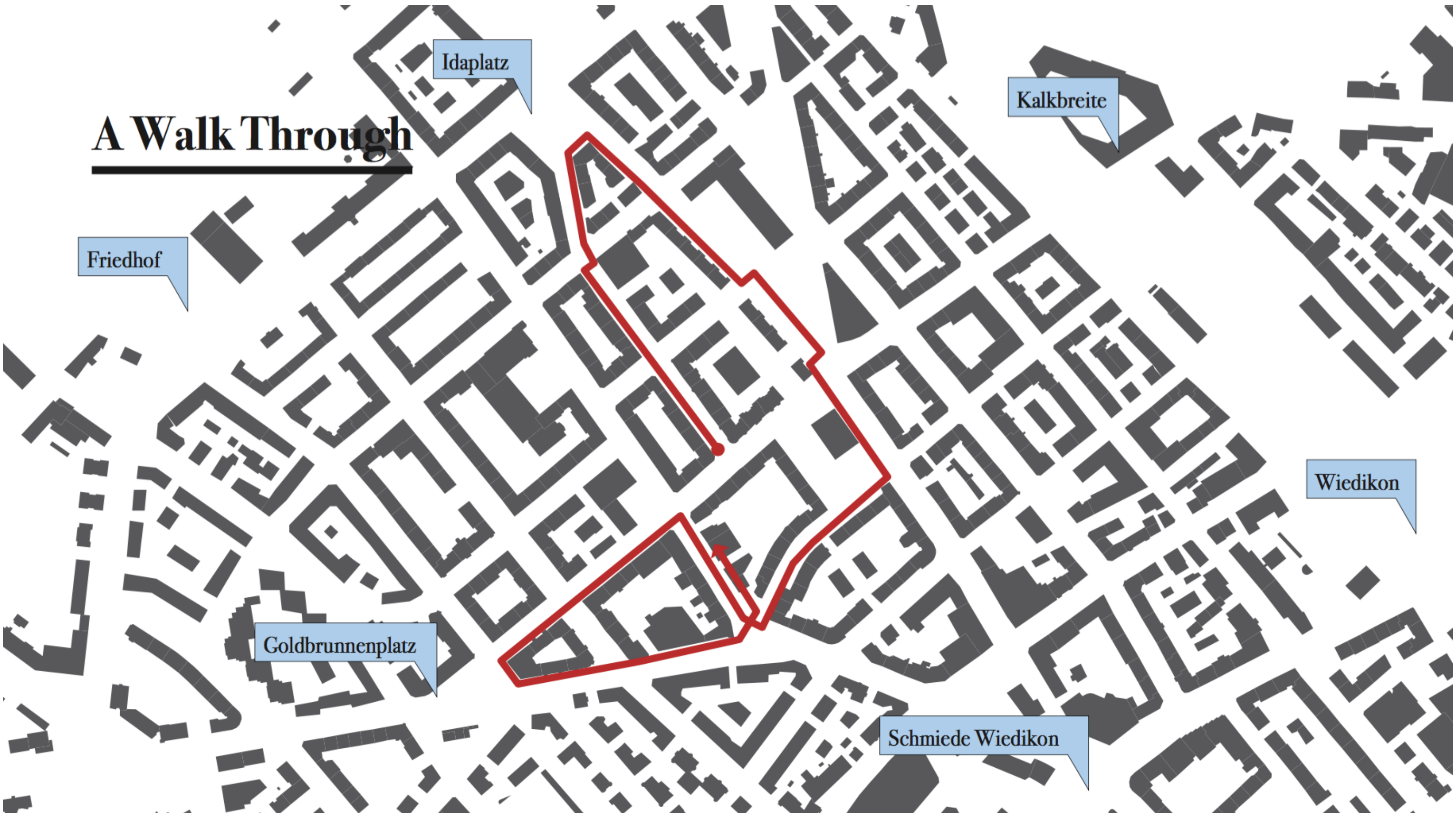


14 Survey points



Best/Worst


Point 1
Point 2
Point 3
Point 4
Point 5
Point 6
Point 7
Point 8
Point 9
Point 10
Point 11
Point 12
Point 13
Point 14


A Walk Through
Idaplatz
Kalkbreite
Friedhof
Wiedikon
Goldbrunnenplatz
Schmiede Wiedikon

Survey points
1
2
3
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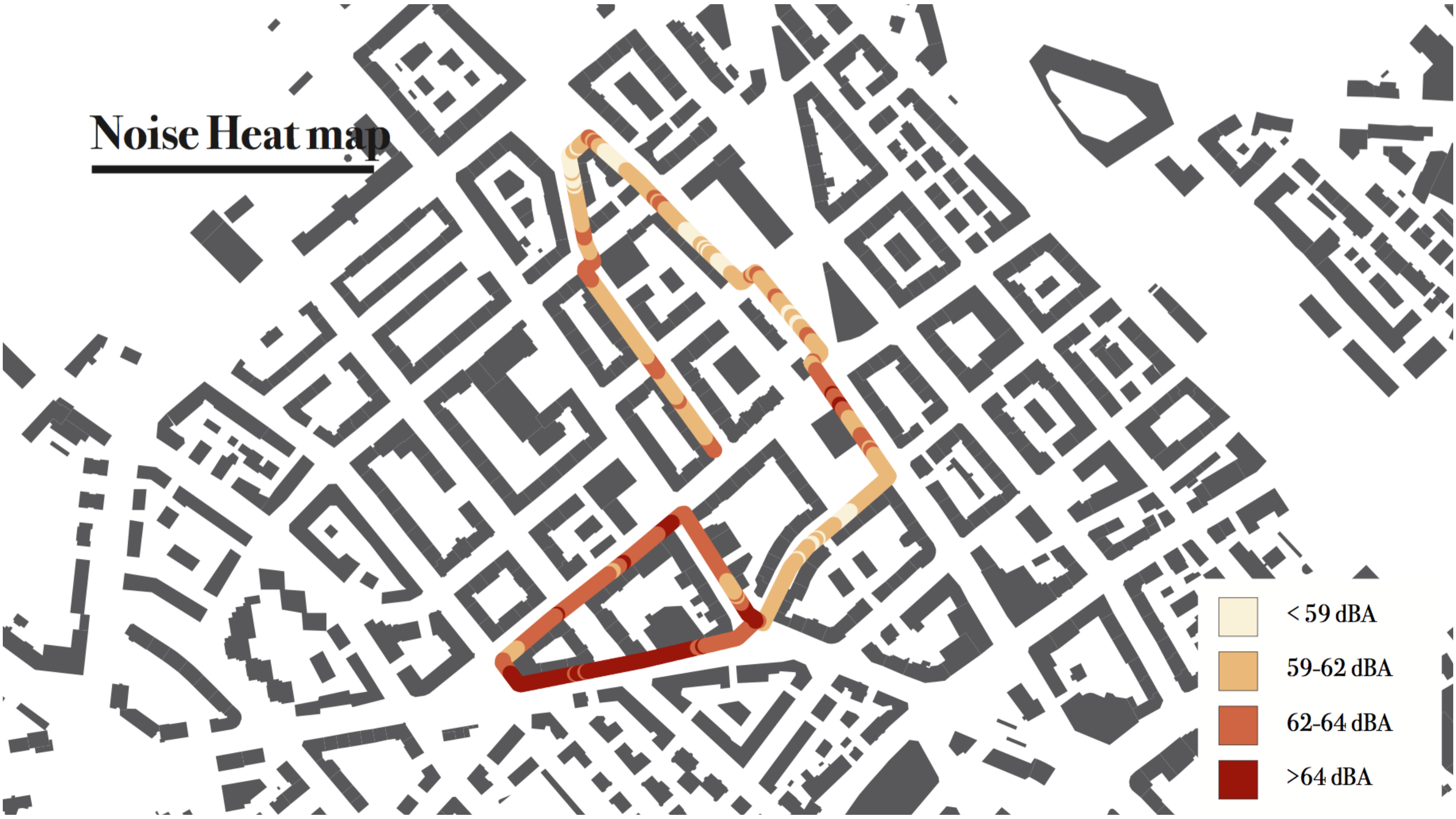
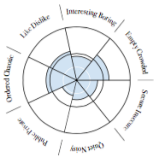
14

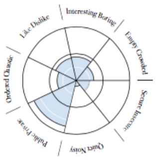

Noise Heat map
< 59 dBA
59-62 dBA
62-64 dBA
>64 dBA

Points Evaluation

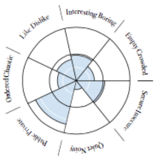
Point 1 62 dBA

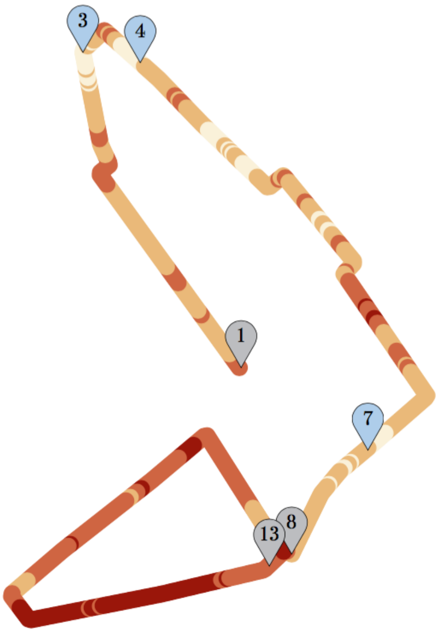


Point 8 64 dBA

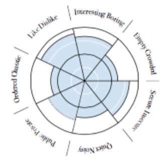


Point 13 63 dBA

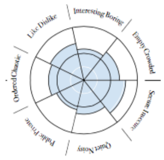




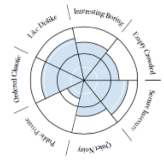
59 dBA Point 3



59 dBA Point 4

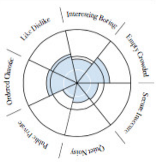


58 dBA Point 7

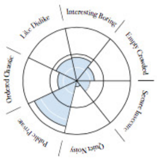


Points Evaluation

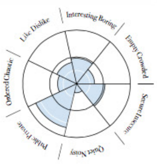
Point 1

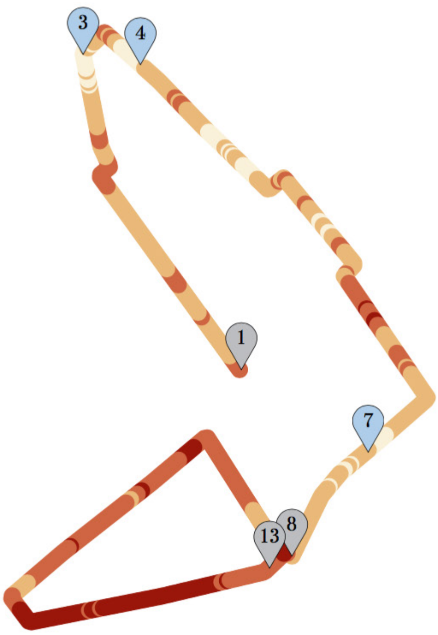


Point 8

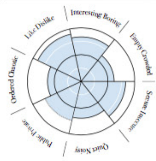


Point 13

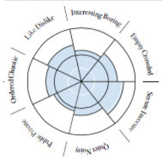




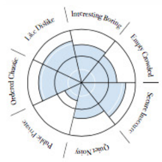
Point 3



Point 4



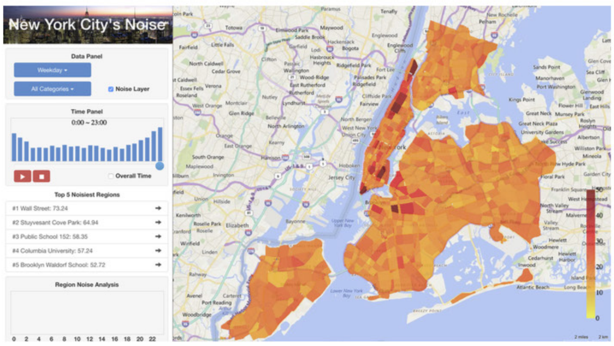
Point 7



Conclusions

- Correlation betweein noise and spatial perception
- BUT: many other factors should be considered: maybe color?
- Zürich is pretty noisy!

References



http://citynoise.azurewebsites.net

https://map.geo.admin.ch

Colour Schemes

Student: Ricardo Joss

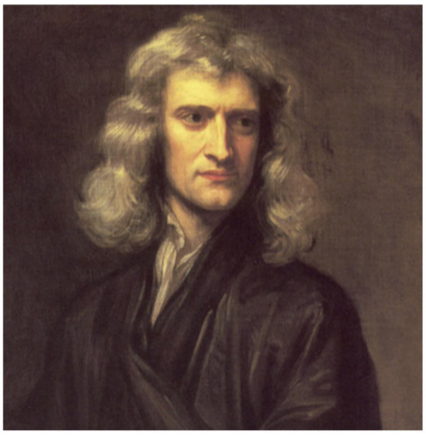
Is there a link of the pure color schemes of a place, to it’s perception of:

beauty / ugliness

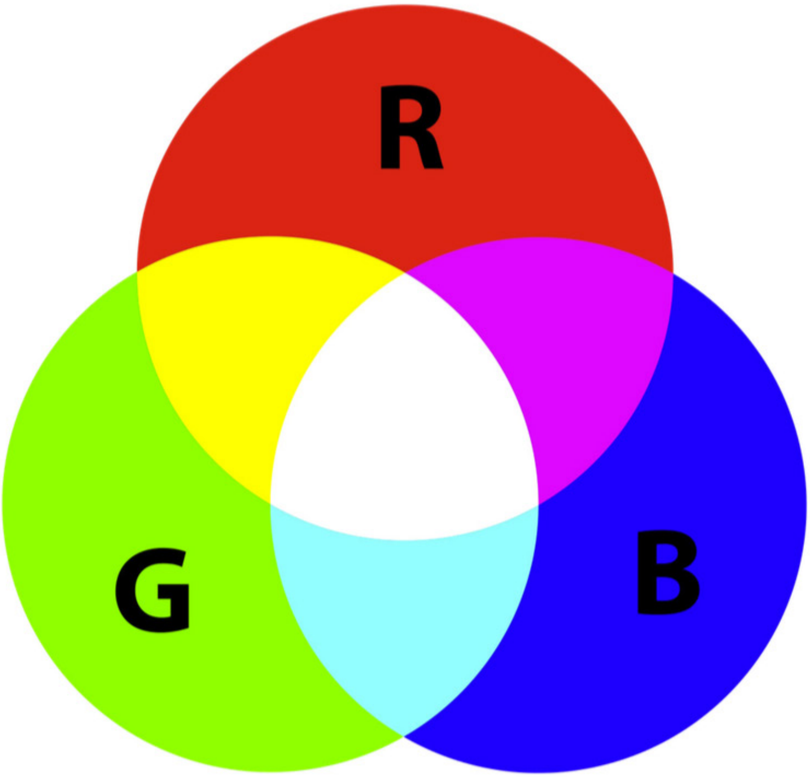
lightness / darkness

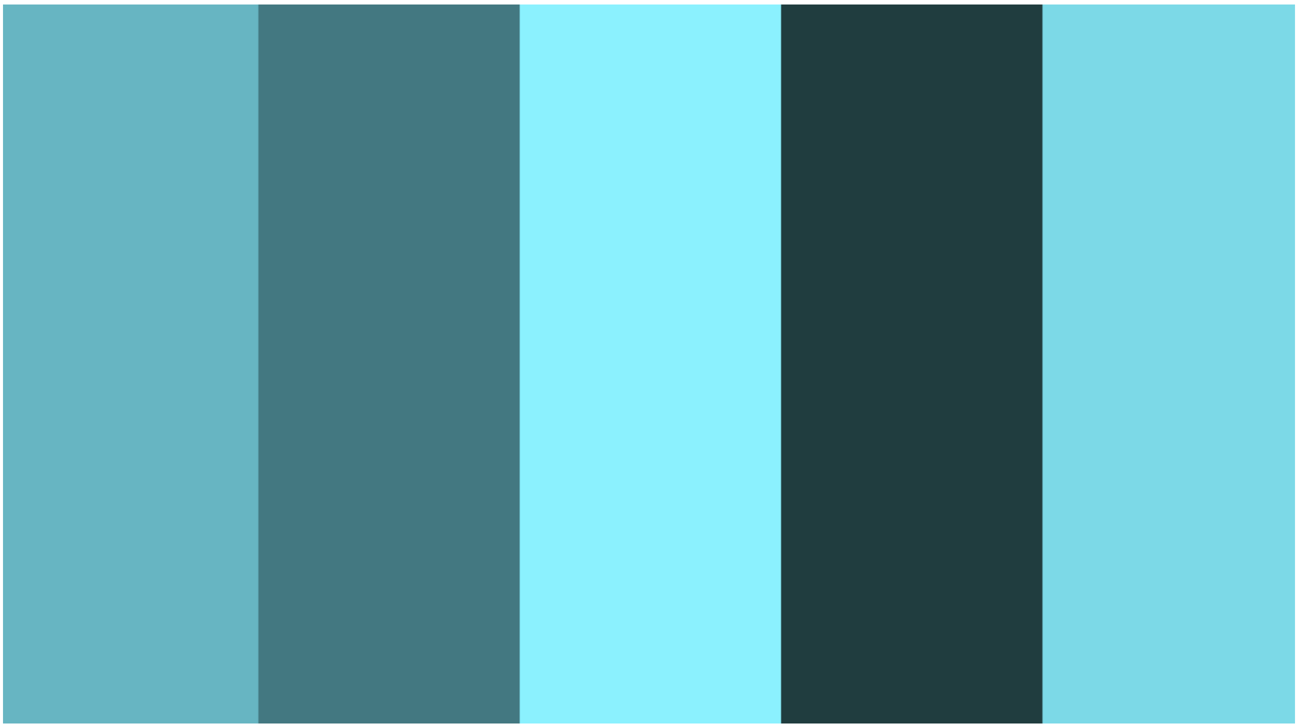
openness / enclosedness

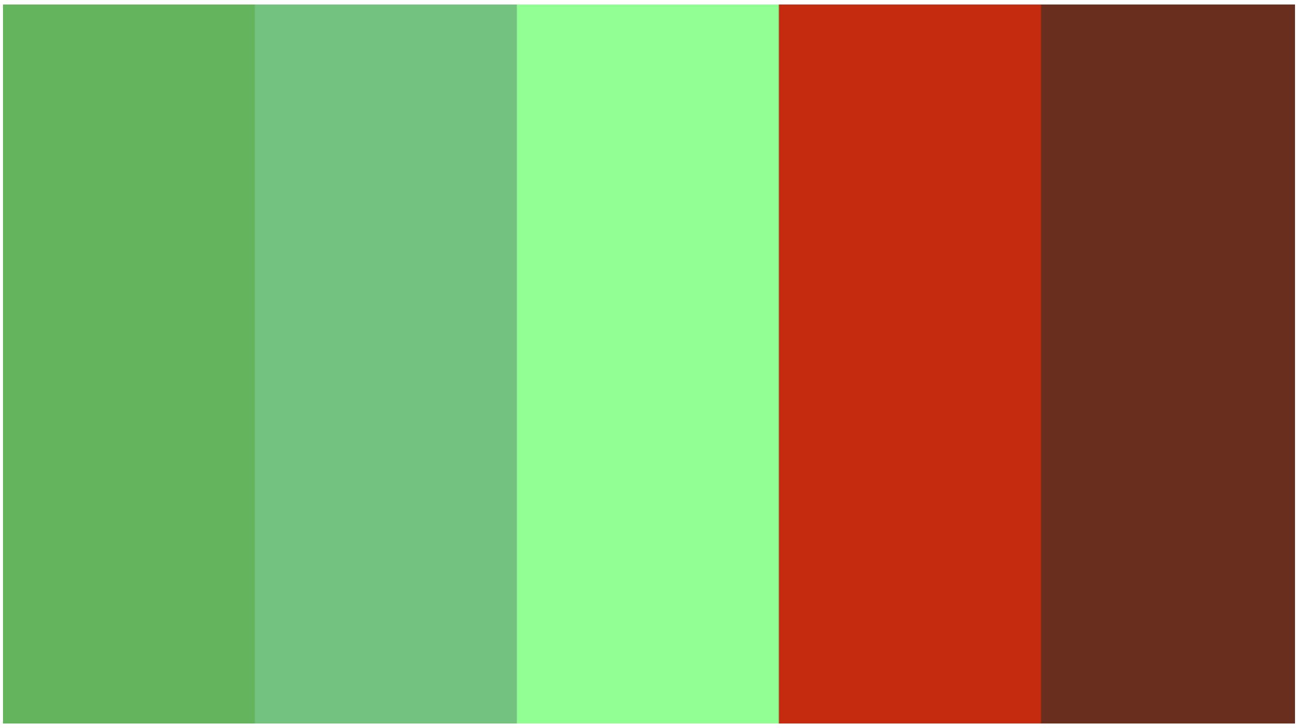
order / chaos

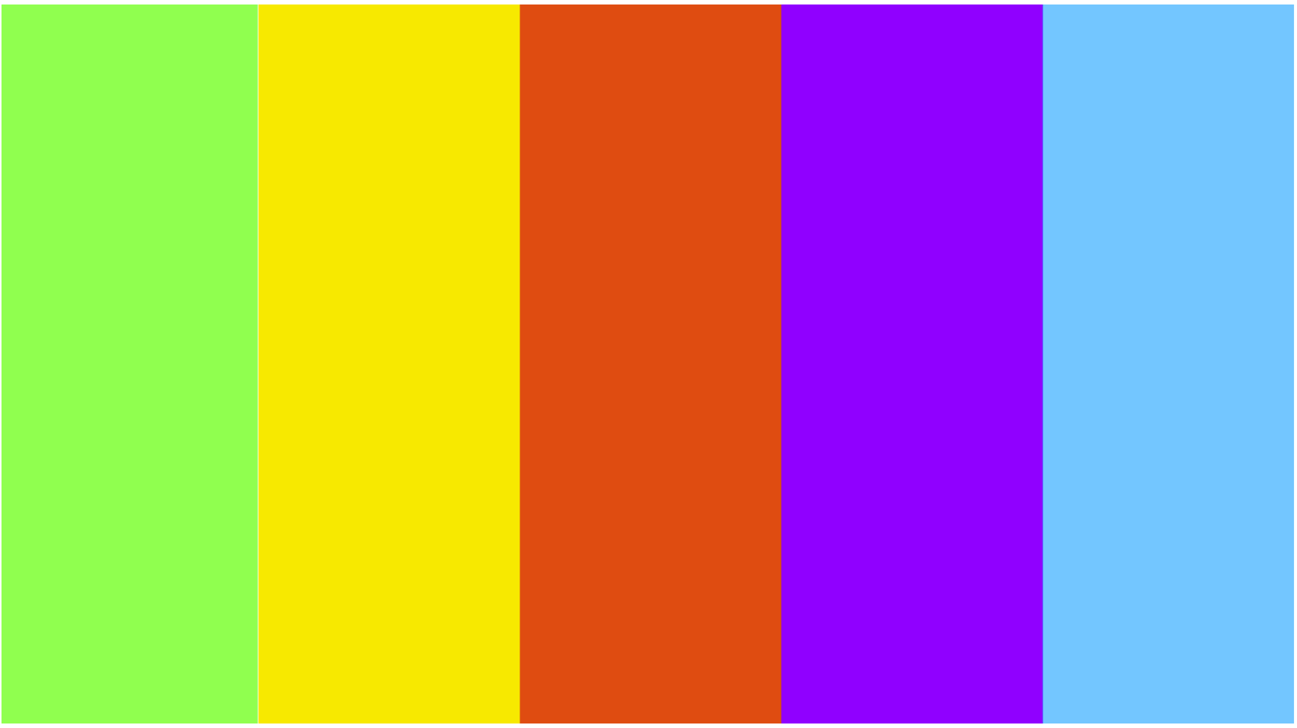


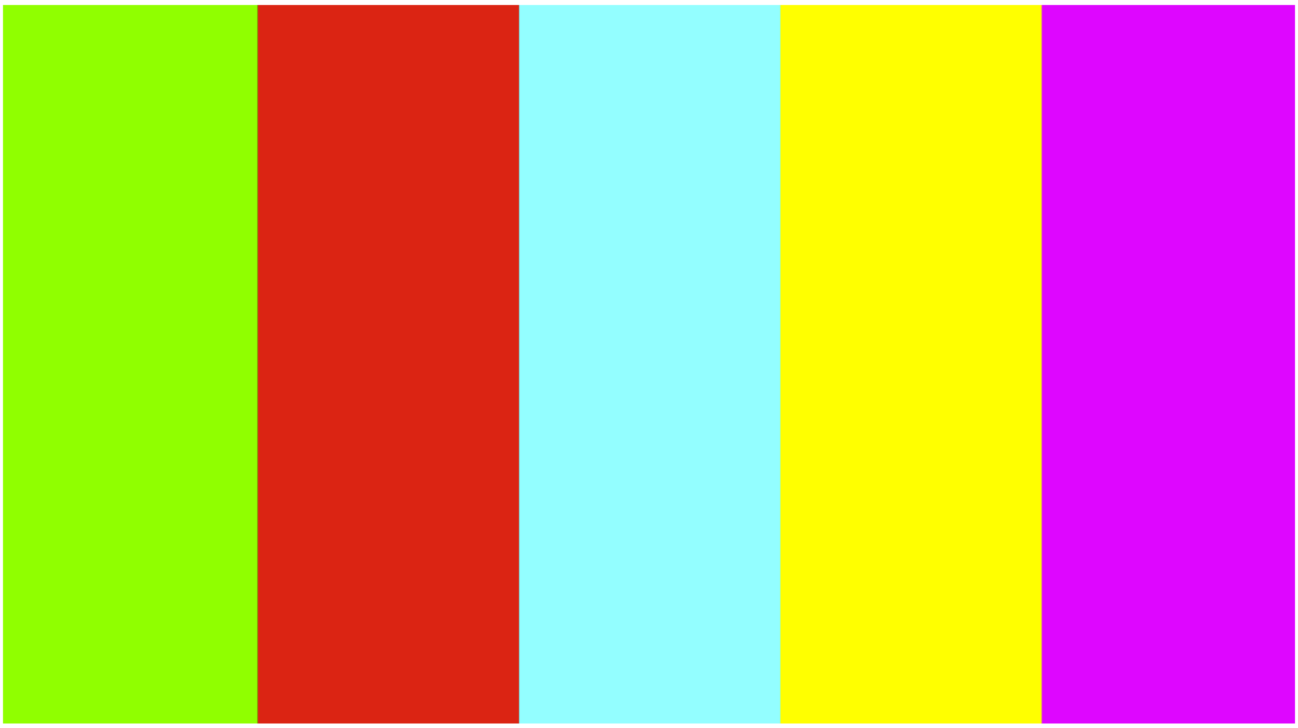

ПИНК ФЛОЙД. ОБРАТНАЯ СТОРОНА ЛУНЫ
PINK FLOYD. THE DARK SIDE OF THE MOON


R
G
B









JMW Turner, Ancient Rome, 1839

Olafur Eliason's Studio

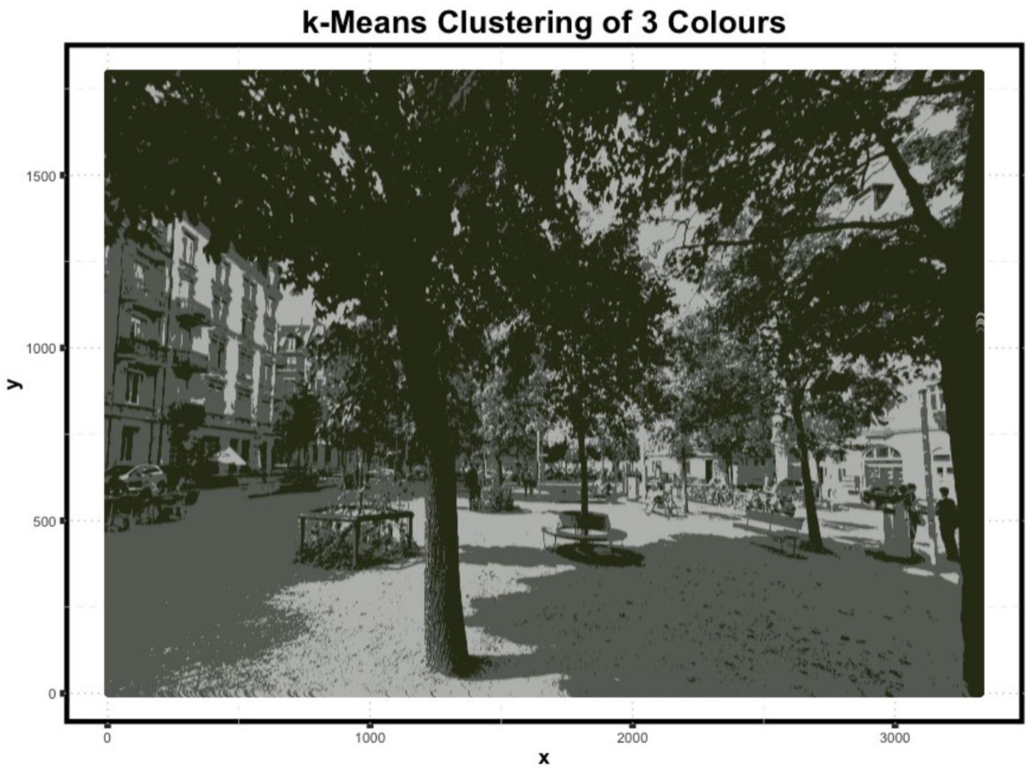
Olafur Eliason, Colour Experiment No. 58, 2014

Method

1. Get a spherical Camera (A smartphone would work as well...)

2. Make a Photosphere of the Place

3. Cluster the colors, to get the most dominant colors. (Test image taken form Google Street View)



4. Run a k-means algorithm in R. Then wait. Then get a coffee. (Calculation time aprox. 30 Minutes)

5. Or just save it in Photoshop as a color reduced PNG-File. (approx. 2 Seconds)

6. Original

7. Again, just the three most dominant colors.

8. 12 most dominant colours.

sketch_160425b

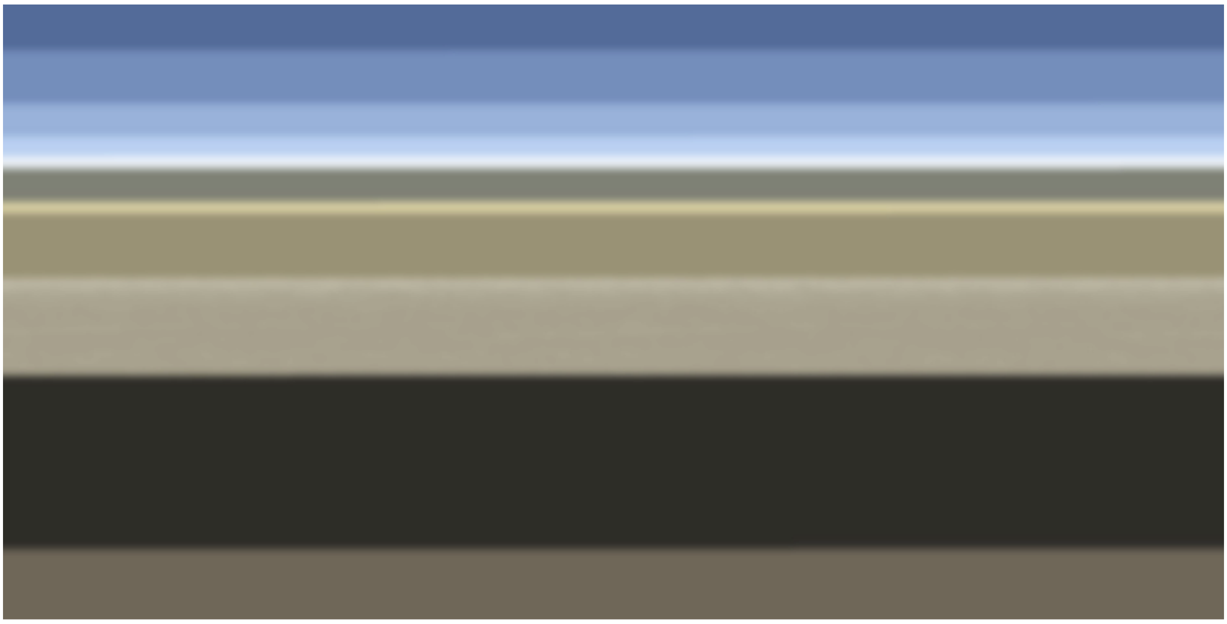
```
import generativedesign.*;
import processing.pdf.*;
import java.util.Calendar;

boolean savePDF = false;

PImage img;
color[] colors;

String sortMode = null;


void setup(){

  //size(3814, 1907); // ESUM Foto-Spheres
  //size(1860, 1046); //16:9 30 Colors
  size(3326, 1794); // WHAT EVER
  //MacBook Pro Retina 15" 2880x1800
  //size(2880, 1800); // Retina
  //size(1920, 1080); // FlyLo
  //size(1108, 598); // half
  //size(3072, 1963); //Turner
  colorMode(HSB, 10, 10, 10, 360);
  noStroke();
  noCursor();
  img = loadImage("Test-Image_12c.png");
  //img = loadImage("j-m-w-turner-ulysses.jpg");
}


void draw(){
  if (savePDF) {
    beginRecord(PDF, timestamp()+".pdf");
    colorMode(HSB, 10, 10, 10, 10);
    noStroke();
  }

  int tileCount = width / max(mouseX, 1);
  float rectSize = width / float(tileCount);

  // get colors from image
  int i = 0;
  colors = new color[tileCount*tileCount];
  for (int gridY=0; gridY<tileCount; gridY++) {
    for (int gridX=0; gridX<tileCount; gridX++) {
      int px = (int) (gridX * rectSize);
      int py = (int) (gridY * rectSize);
      colors[i] = img.get(px, py);
      i++;
    }
  }

  // sort colors
  if (sortMode != null) colors = GenerativeDesign.sortColors(this, colors, sortMode);


  // draw grid
  i = 0;
  for (int gridY=0; gridY<tileCount; gridY++) {
    for (int gridX=0; gridX<tileCount; gridX++) {
      fill(colors[i]);
      rect(gridX*rectSize, gridY*rectSize, rectSize, rectSize);
      i++;
    }
  }

  if (savePDF) {
    savePDF = false;
    endRecord();
  }
}
```

Pixel sorting algorithm in Processing. Sorting by Hue-Value.

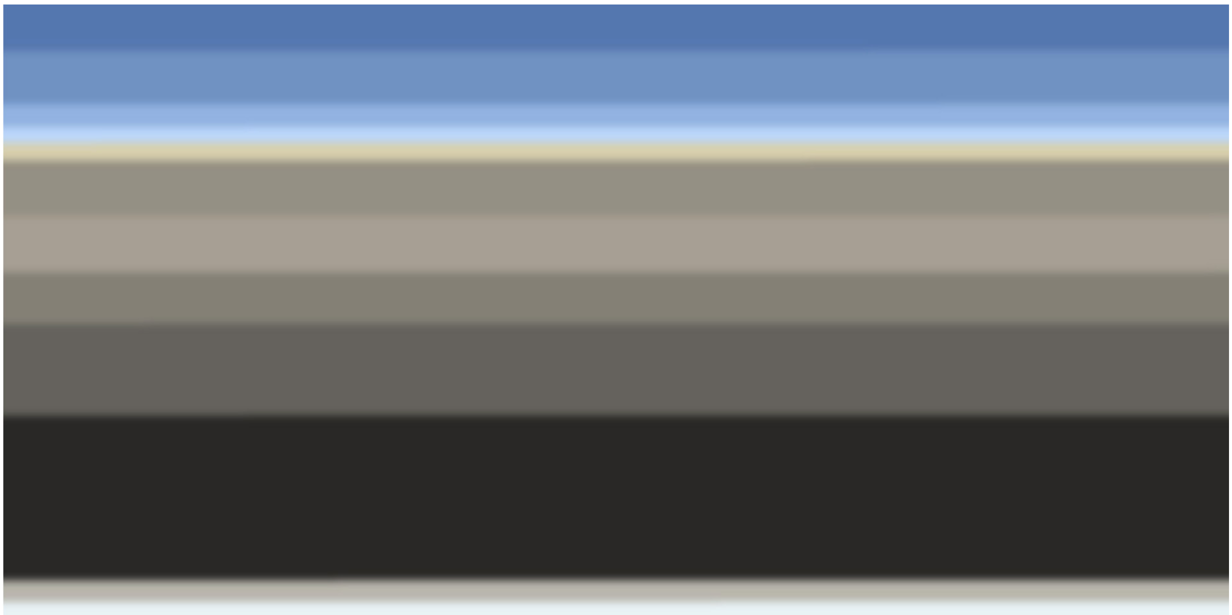
12 most dominant colors sorted by Hue.

Without clustering. All colors are present. Sorted by Hue.

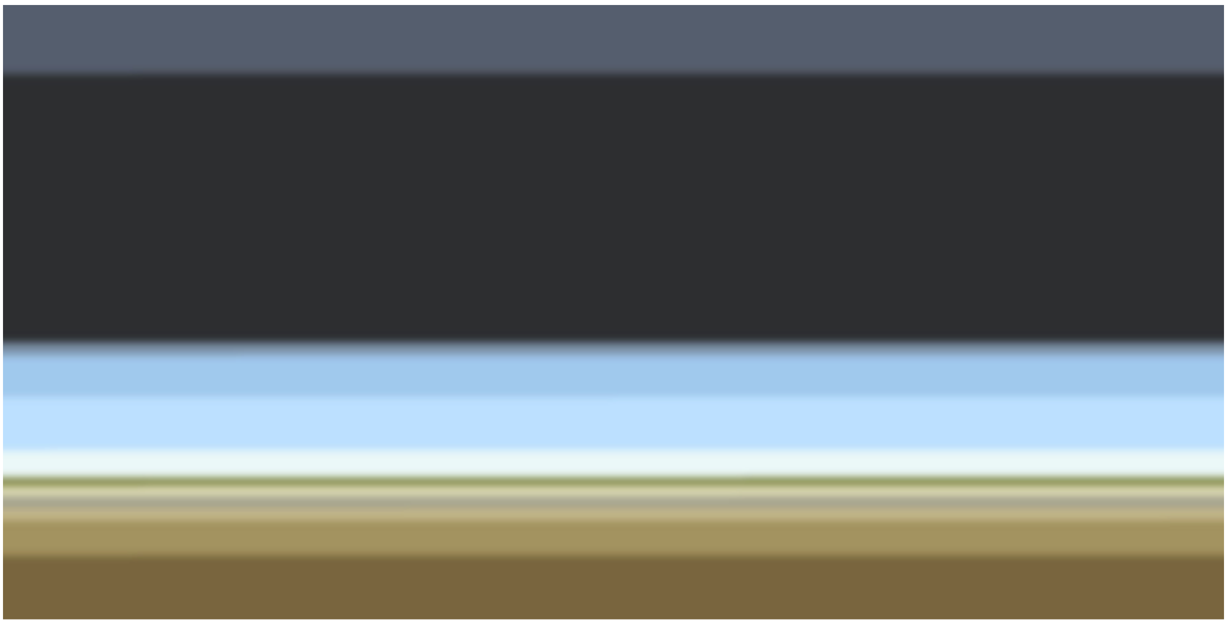
12 most dominant Colors sorted by Hue with Gaussian-Blur of 12 Pixels.



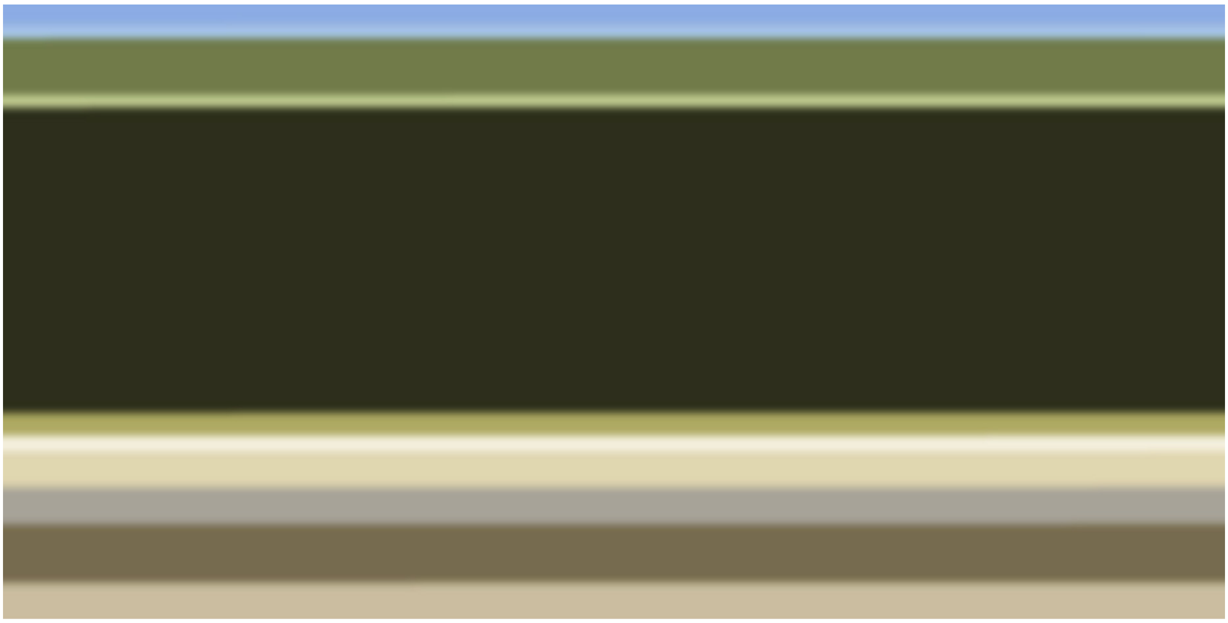
Position 1 - 12 Colors



Position 2 - 12 Colors



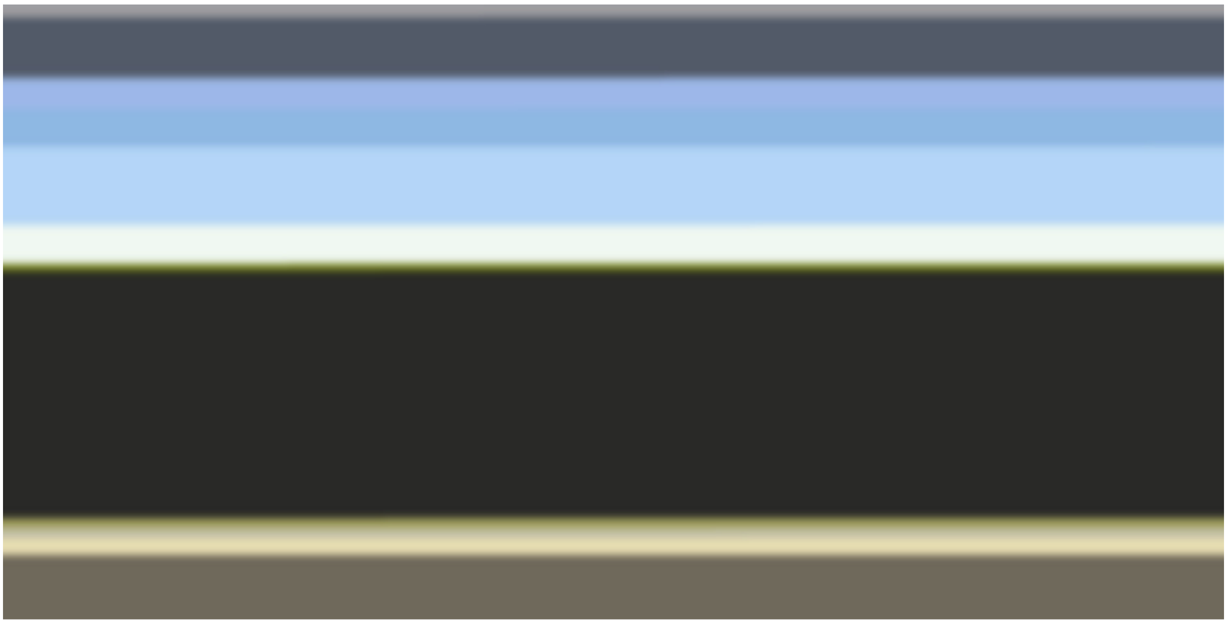
Position 3 - 12 Colors



Position 4 - 12 Colors

Position 5 - 12 Colors

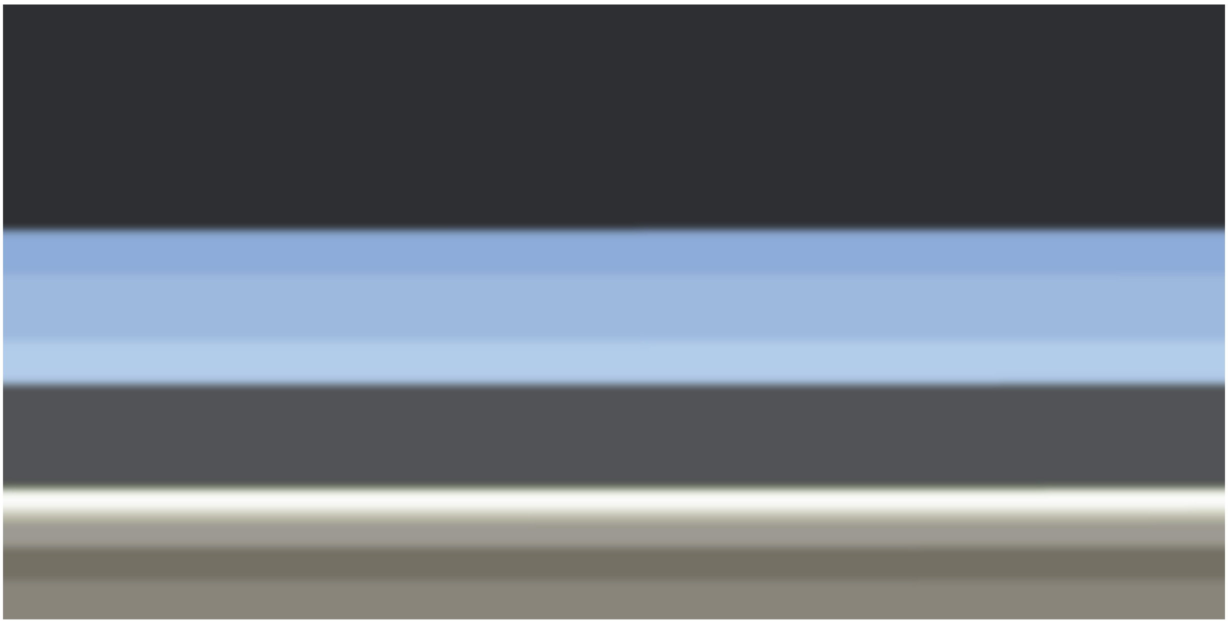
Position 6 - 12 Colors



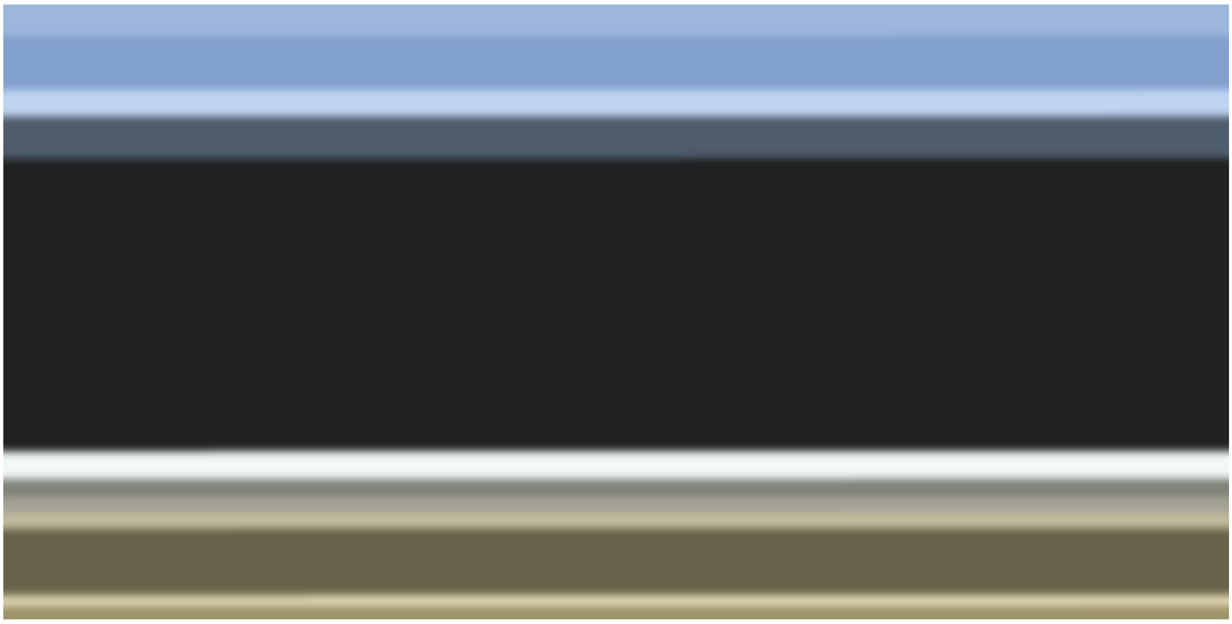
Position 7 - 12 Colors

Position 8 - 12 Colors

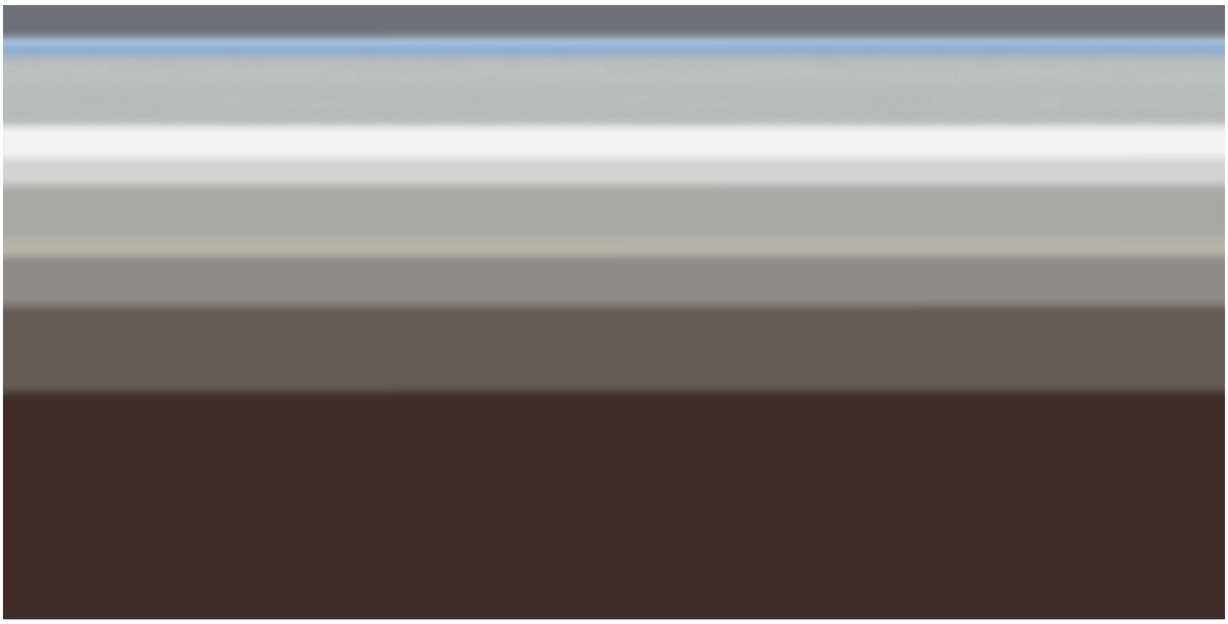
Position 9 - 12 Colors



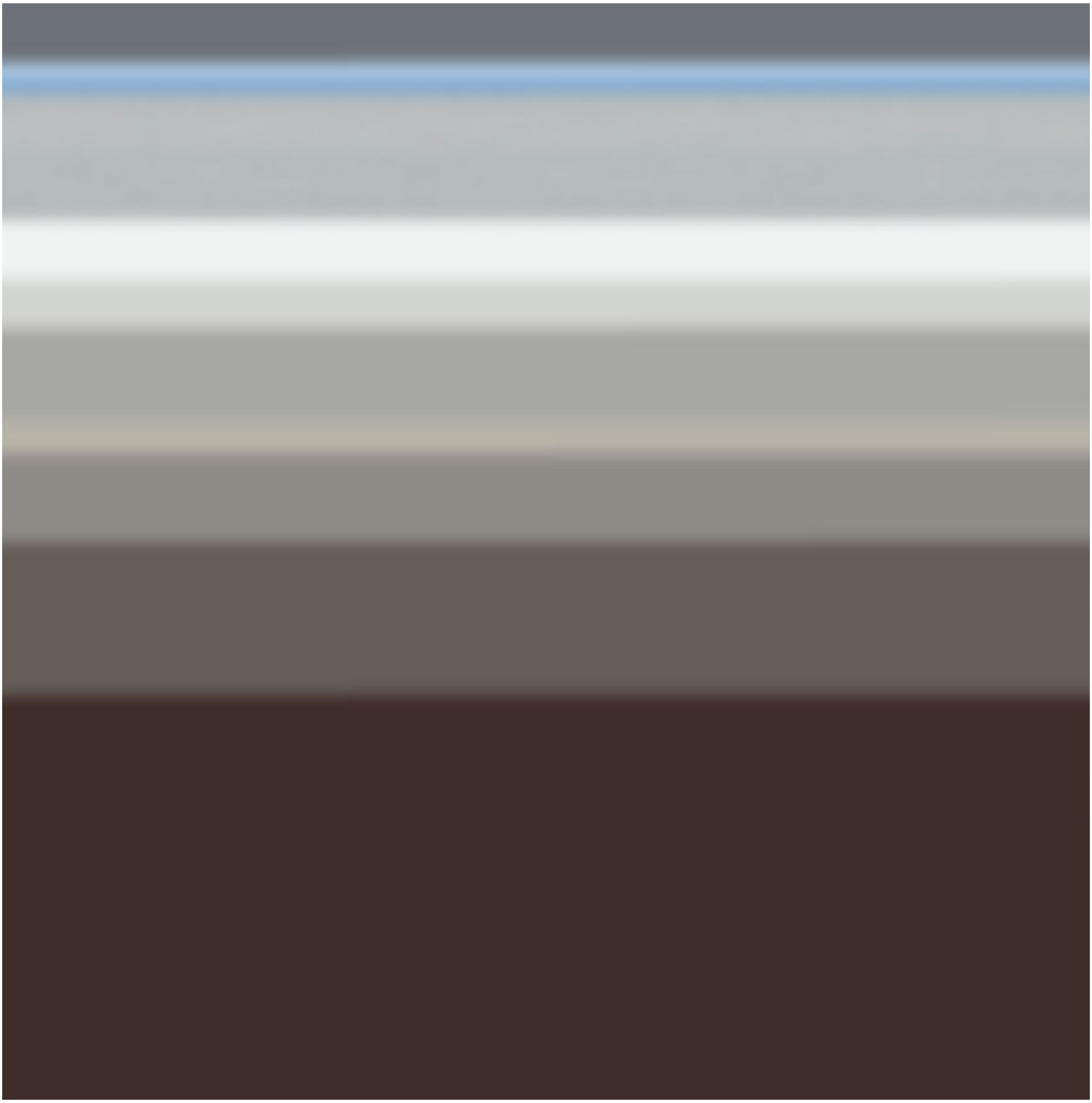
Position 10 - 12 Colors



Position 11 - 12 Colors

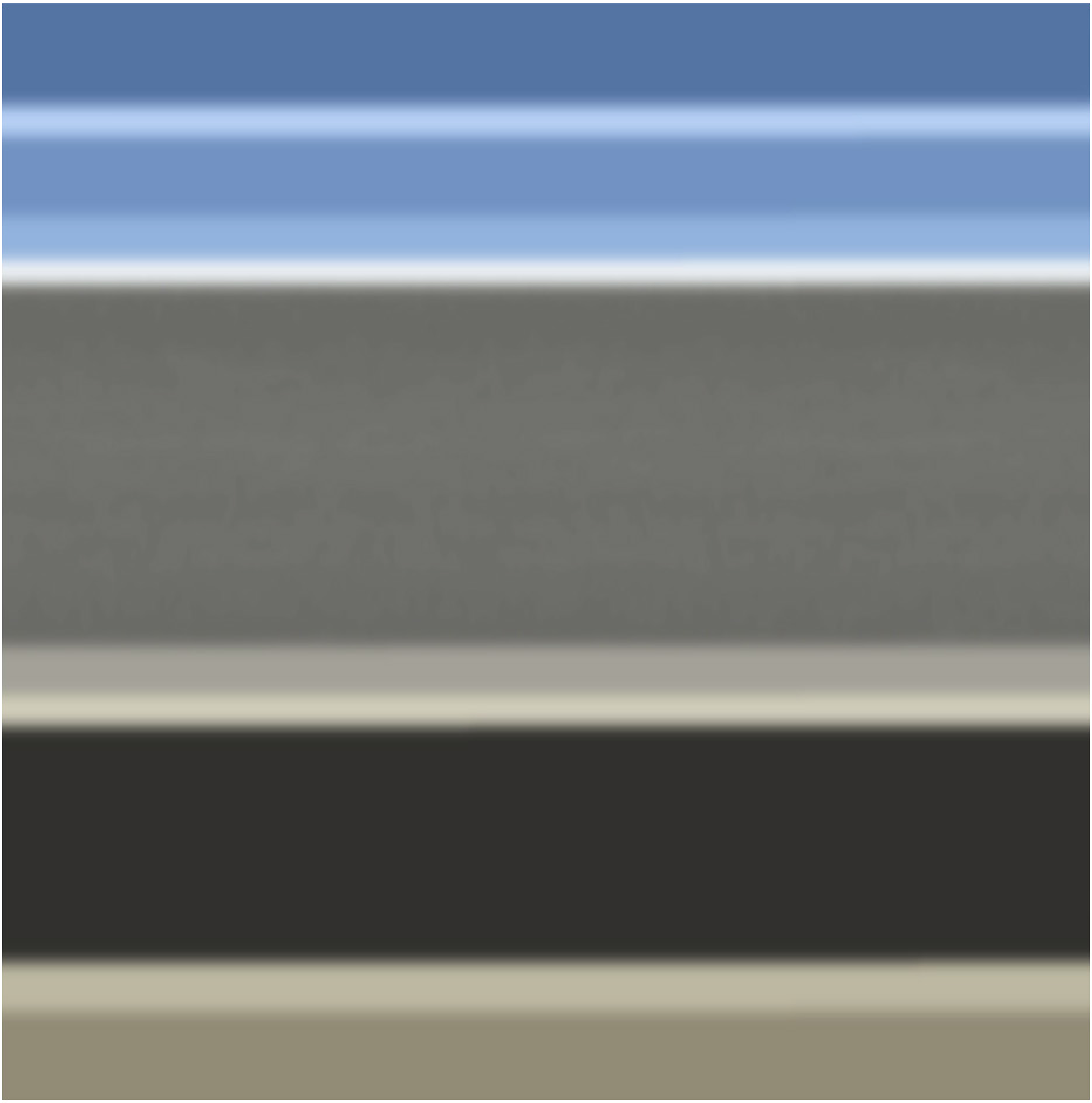


Position 12 - 12 Colors - Red Sunblind



12 Colors

Position 12, Red Sunblind

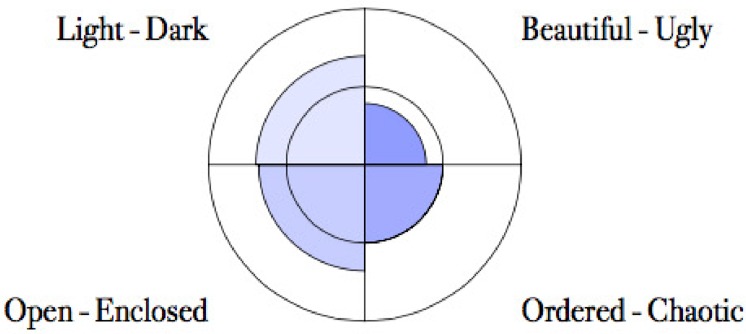


12 Colors

Position 12, Sky

Outstanding Positions according to the survey

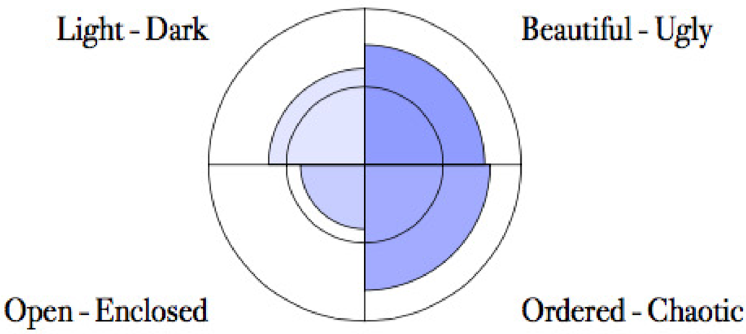
12 Colors



Position 5, rated as ugliest

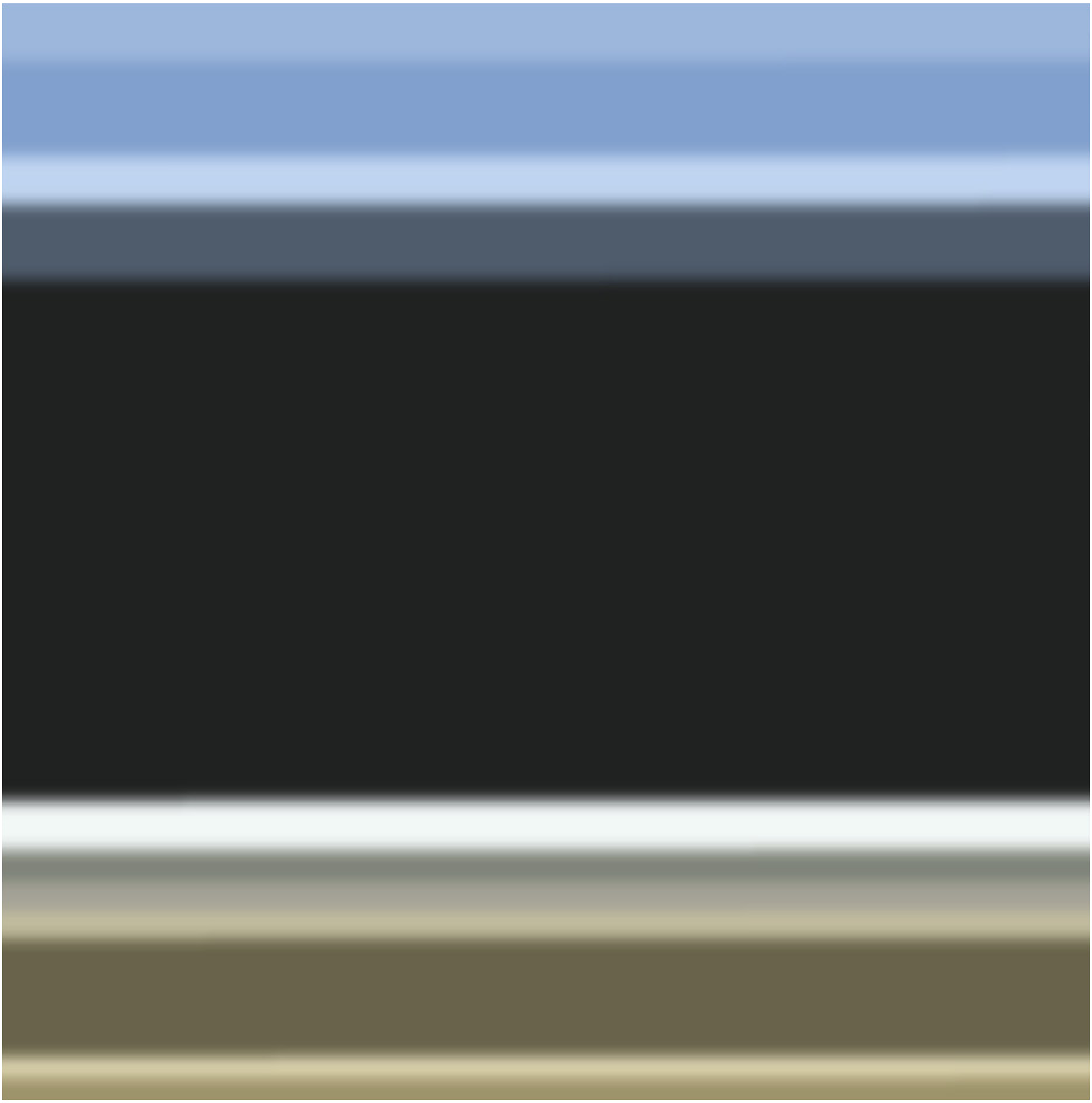
12 Colors

12 Colors

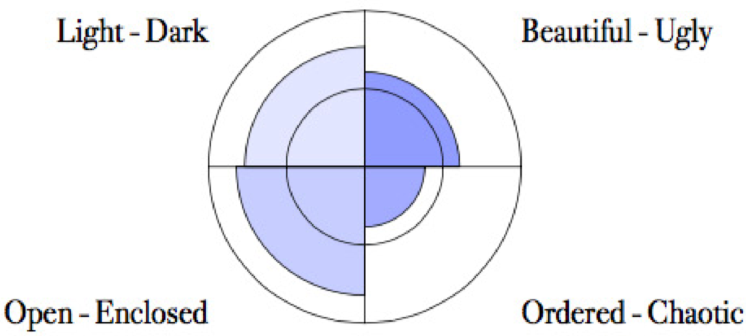


Position 7, rated as enclosest

12 Colors

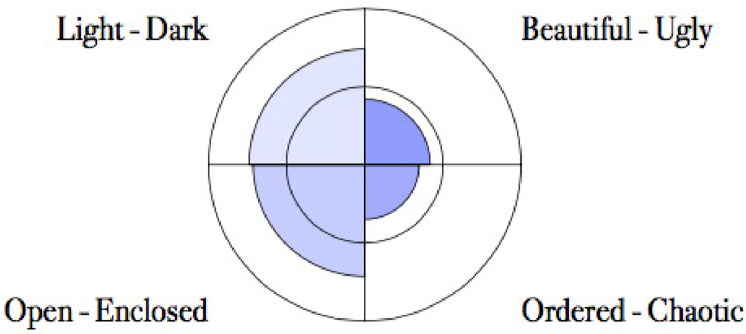


12 Colors



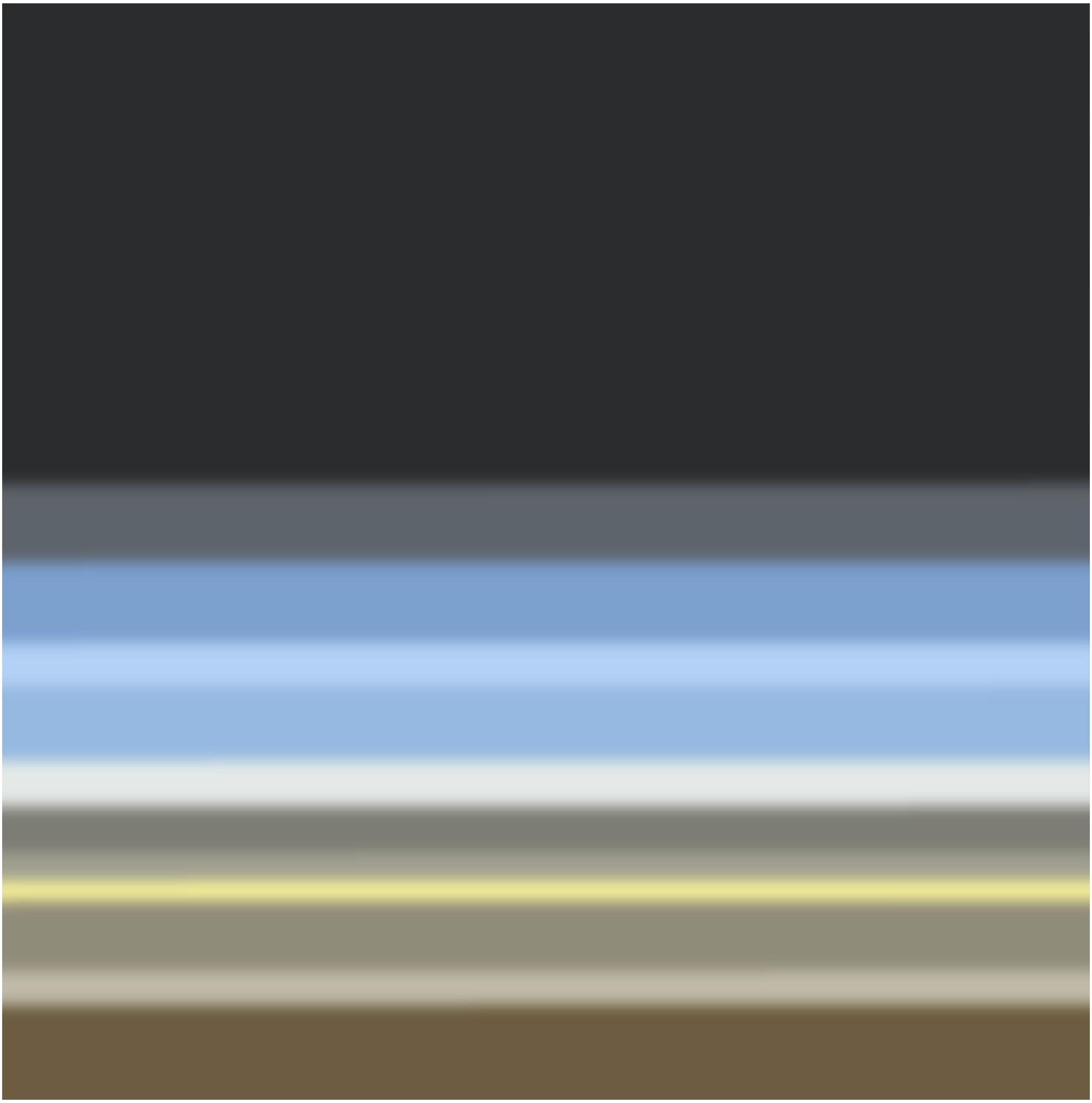
Position 11, rated as most open

12 Colors

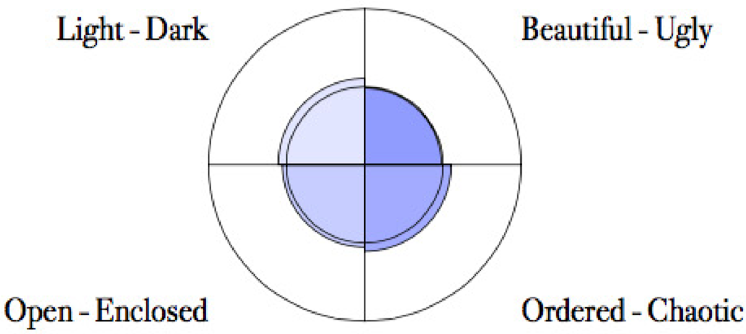


Position 13, rated as most chaotic

12 Colors

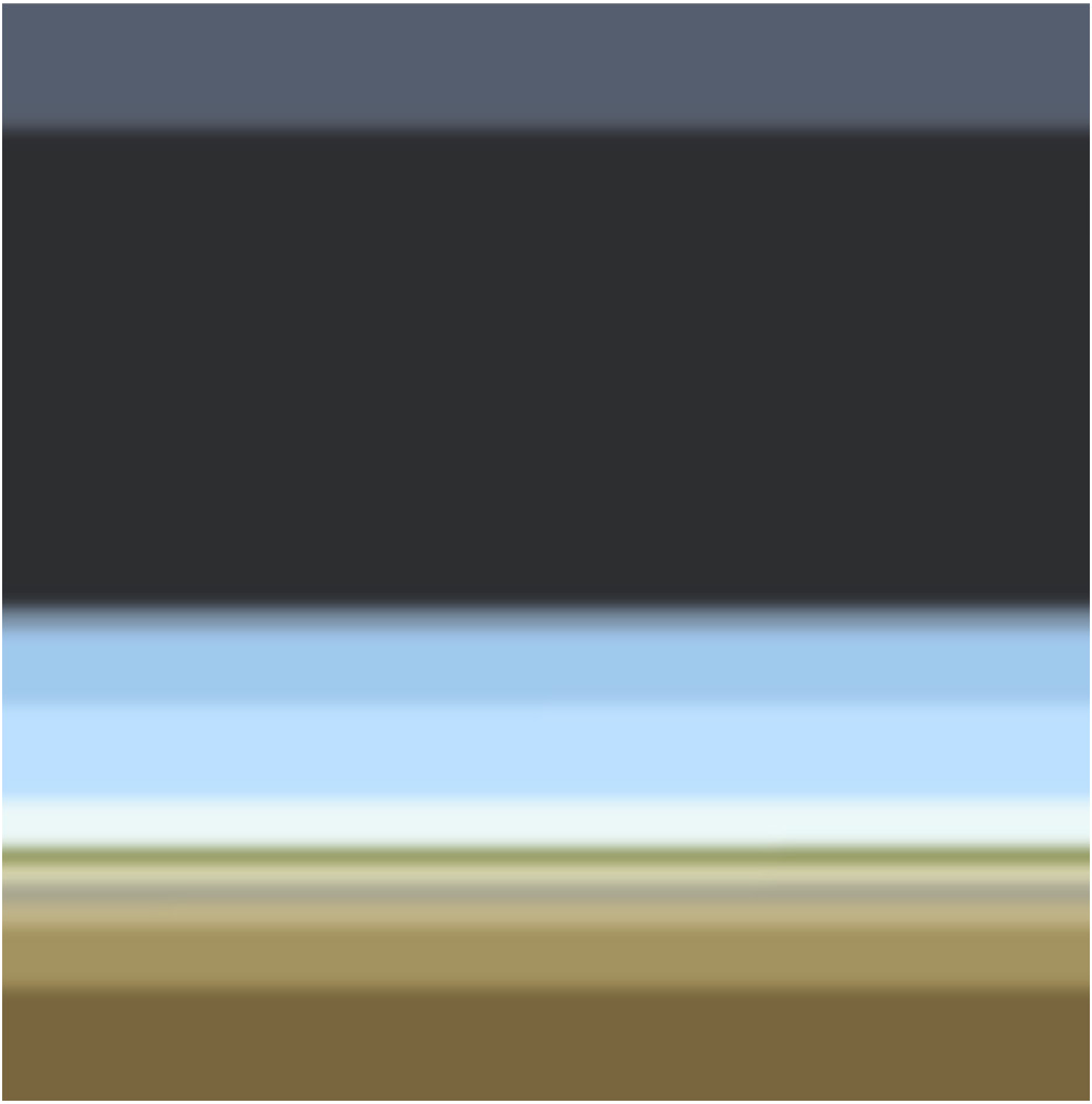


12 Colors



Position 14, rated as darkest

Best & Worst according to the survey



Most Beautiful

Position 3 + 64%

Ugliest

Position 5 - 22%

Ugliest

Position 5 - 22%

Lightest

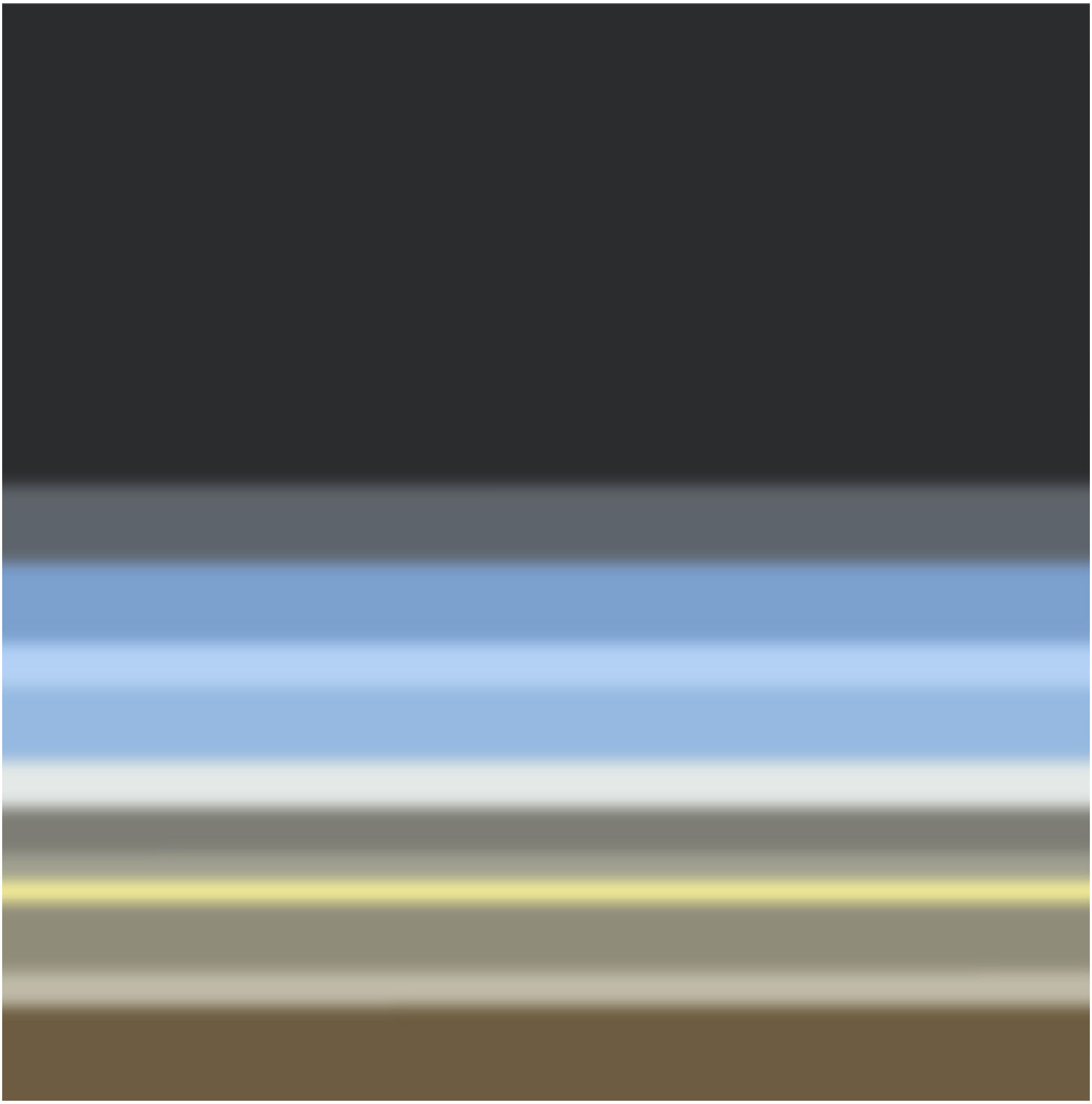
Position 3 + 66%

Lightest

Position 3 + 66%

<u>Darkest</u>

Position 14 + 11%



<u>Darkest</u>

Position 14 + 11%

Most Open

Position 11 + 65%

<u>Most Enclosed</u>

Position 7 - 18%

Position 7 + 61%

Most Structured

Position 7 + 61%

Most Chaotic

Most Chaotic

Position 13 - 31%

Overall best

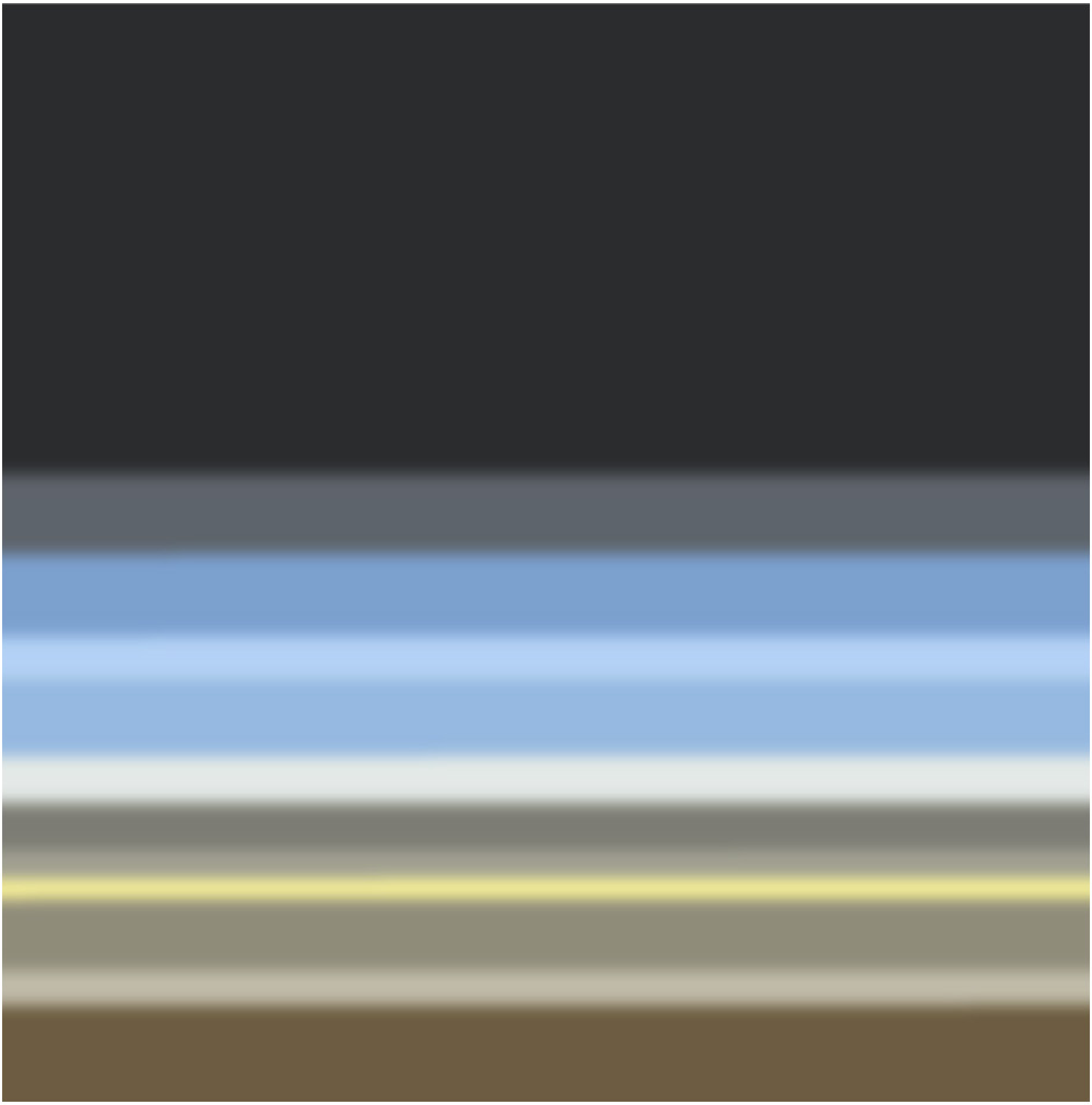
Position 3 + 55%

Overall best

Position 3 + 55%

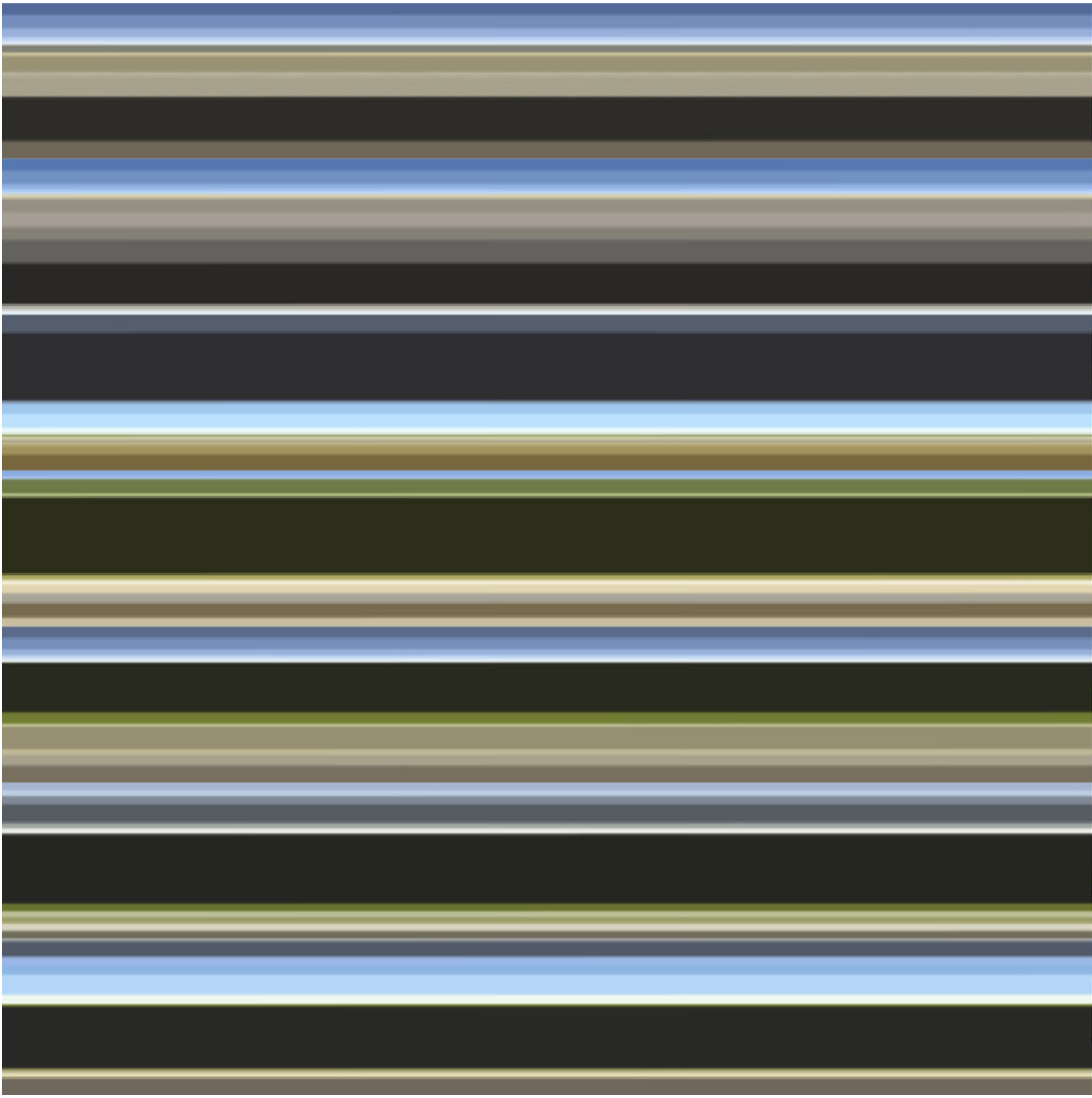
Overall worst

Position 9 + 4%

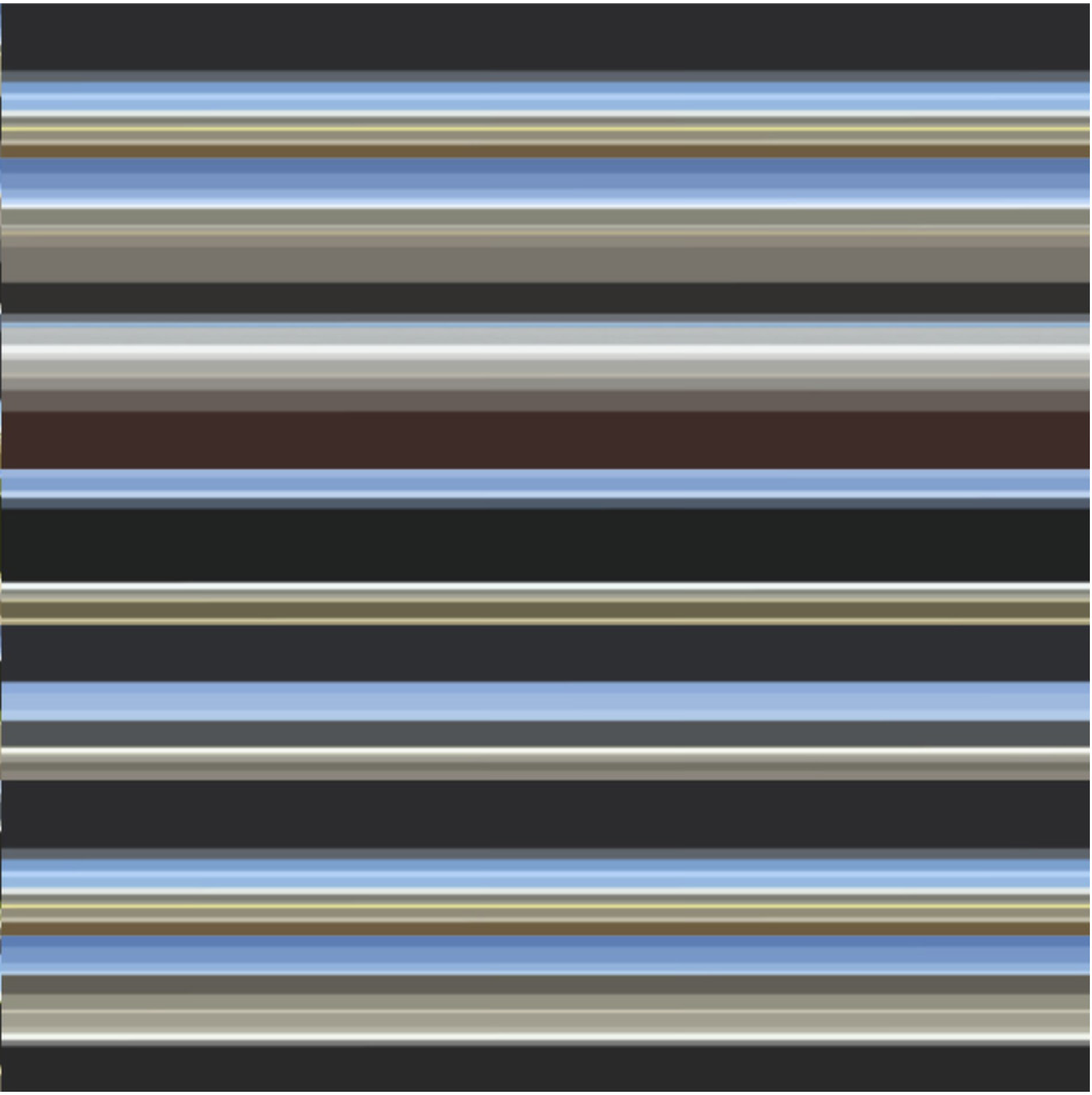


Overall worst

Position 9 + 4%



All 14 Positions



All Positions - 12 Most dominant Colors

Is there a link of the pure color schemes of a place, to it’s perception of:

beauty / ugliness

lightness / darkness

openness / enclosedness

order / chaos

Hard to say. Because...

- big difference in daytime, weather, etc.

- spherical distortion

- no color metering, white and color balance, etc.

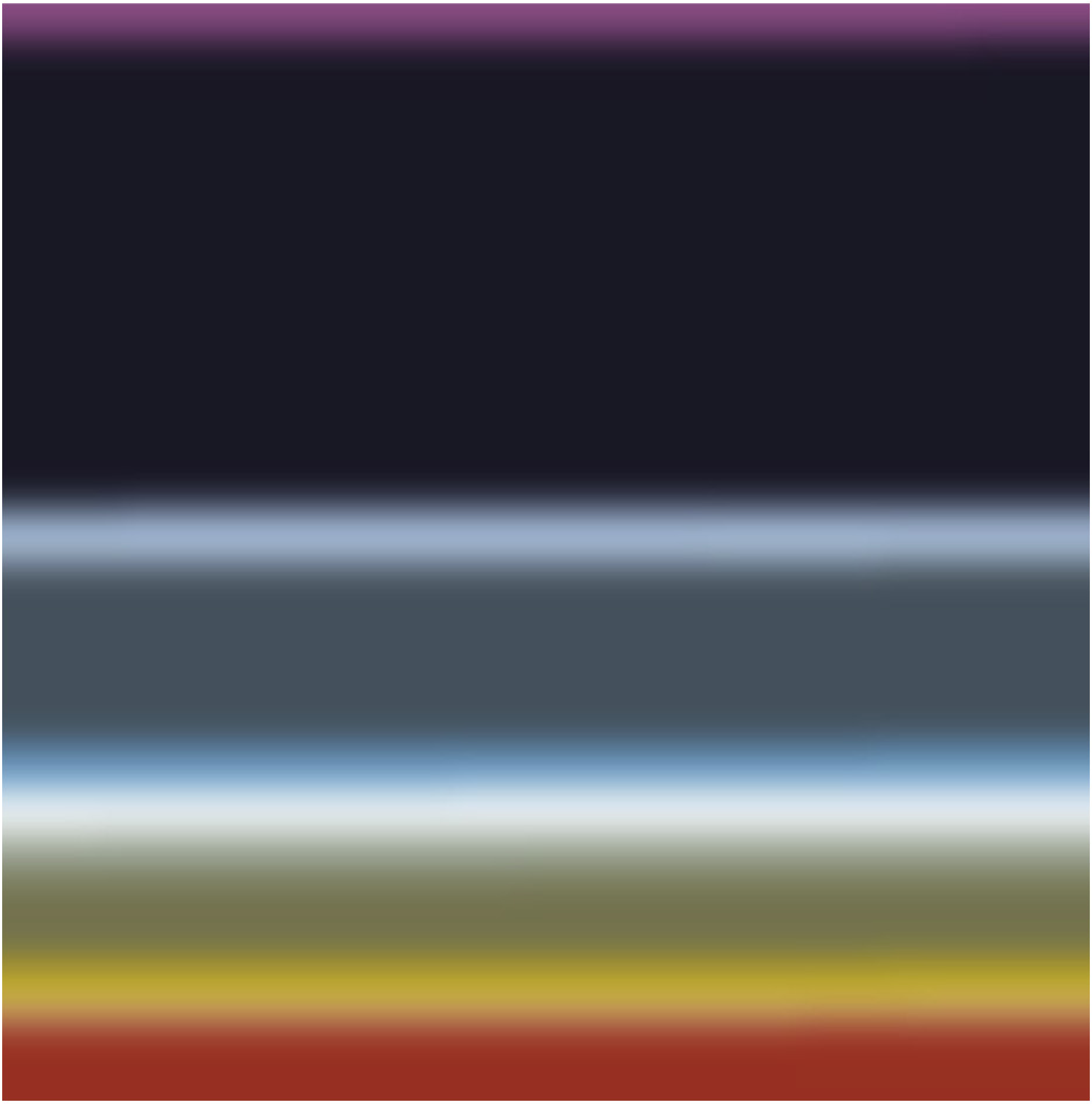
- camera is specific to one point

- people judge not by point but by place

- neither green (plants) or blue (clear sky) influence

... and just for fun:

12 Colors



12 Colors

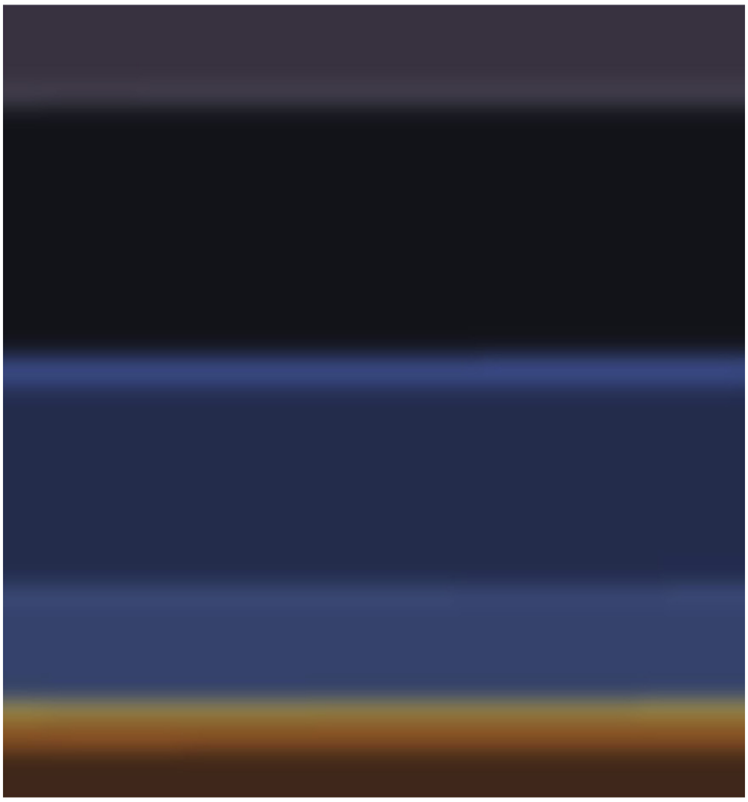
Shinjuku, Tokyo, JP

12 Colors

12 Colors

Rainbow Road, Mario Kart 64, Nintendo 1996

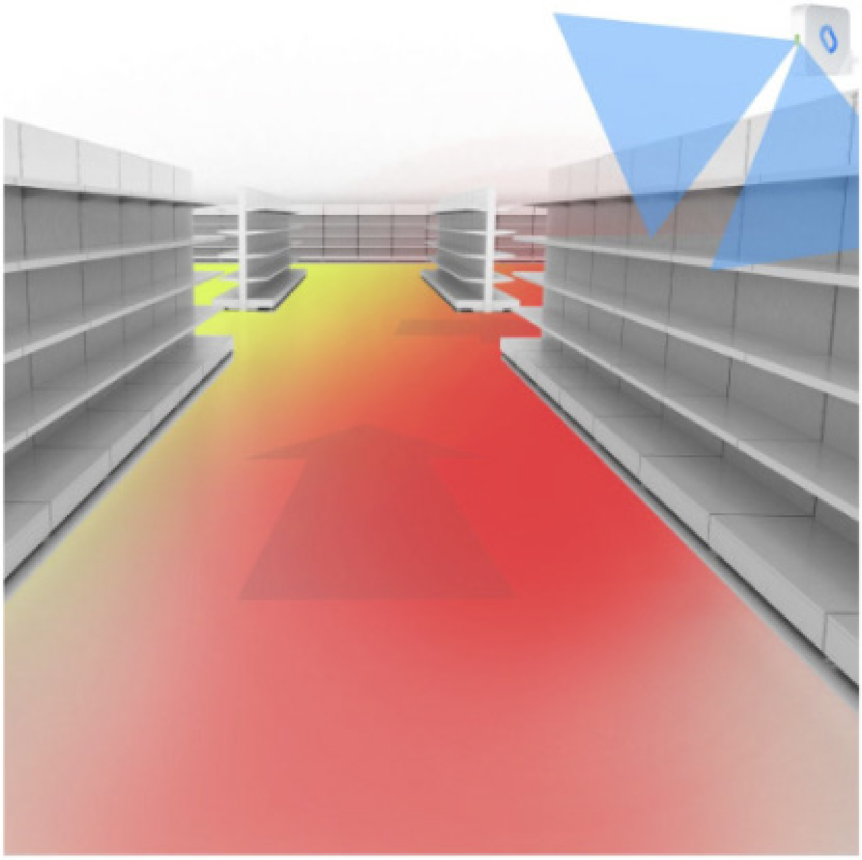
Favela by Day, 12 Colors



Favela by Night, 12 Colors

Crowds

Student: Robert Schiemann



Example: “Sensalytics”

Counting visitors, finding Hot-spots, knowing location details.
Suitable for stationary stores, events, fairs and public buildings.

Source: https://sensalytics.net/en

Example: “Sensalytics”

Get data in real-time.

Source: https://sensalytics.net/en

Urban WiFi Characterization via Mobile Crowdsensing

Arsham Farshad and Mahesh K. Marina
The University of Edinburgh

Francisco Garcia
Agilent Technologies

***Abstract*—We present a mobile crowdsensing approach for urban WiFi characterization that leverages commodity smartphones and the natural mobility of people. Specifically, we report measurement results obtained for Edinburgh, a representative European city, on detecting the presence of deployed WiFi APs via the mobile crowdsensing approach. They show that few channels in 2.4GHz are heavily used; in contrast, there is hardly any activity in the 5GHz band even though relatively it has a greater number of available channels. Spatial analysis of spectrum usage reveals that mutual interference among nearby APs operating in the same channel can be a serious problem with around 10 APs contending with each other in many locations. We find that the characteristics of WiFi deployments at city-scale are similar to that of WiFi deployments in public spaces of different indoor environments. We validate our approach in comparison with wardriving, and also show that our findings generally match with previous studies based on other measurement approaches. As an application of the mobile crowdsensing based urban WiFi monitoring, we outline a cloud based WiFi router configuration service for better interference management with global awareness in urban areas.**

I. Introduction

Significant interest in mobile phone sensing in recent years can be attributed to several factors, including: their ubiquitous nature; rapid evolution toward smartphones with several built-in sensors; carried by humans, making them natural to be used for "mobile" sensing; and the possibility of leveraging the cloud via several available connectivity options for computing power, storage and "centralization". Not surprisingly then, mobile phone sensing applications have been realized or envisioned in diverse domains (e.g., transportation, social networking, health monitoring) [1], [2]. When a group/community of participants (a *crowd*) is engaged with suitable incentives, mobile phone sensing becomes even more compelling for continual and fine-grained spatio-temporal monitoring of the phenomenon of interest in a *cost-effective* manner. Indeed, as Xiao et al. note in [3], the focus of mobile sensing research and applications is shifting towards *mobile crowdsensing*, which is defined as "individuals with sensing and computing devices collectively share data and extract information to measure and map phenomena of common interest" [4]. Several mobile crowdsensing applications have been developed and deployed (e.g., [5], [6]) and it remains a very active area of research.

We consider the application of the mobile crowdsensing paradigm to wireless network monitoring. Besides the many sensors, modern mobile phones feature several wireless network interfaces as connectivity options (e.g., cellular, WiFi, Bluetooth, NFC). Discussions of mobile phone sensing have been mostly centered around the use of built-in sensors and/or specialized add-on sensors (e.g., GasMobile [5], CellScope[1], NETRA[2]) with connectivity options serving as a means for data sharing (see [2], for example). We expand this commonly held view to treat network interfaces also as sensors. GPS, which is an integral part of all smartphones today, presents an example of a network interface that sits at the boundary of these two views — GPS is seen as a location sensor for mobile phone sensing applications whereas it is actually a RF communication system in which GPS receiver on a phone uses signals transmitted from satellites for localization. Technical specifications of some smartphones do acknowledge this view. See [7], for example. A more obvious example is the use of cellular interface on smartphones for crowdsourcing based active/passive measurement of mobile networks as in [8], [9]. As yet another example, in a recent work [10], we developed a system that exploits the WiFi interface on smartphones for low-cost and automated monitoring of WiFi networks in indoor environments like enterprises and public buildings (e.g., shopping malls).

In this paper, we focus on mobile crowdsensing based characterization of WiFi deployment and configuration in urban areas at a city level using the WiFi interface on smartphones as a measurement sensor. Specifically, we report results from a mobile crowdsensing based WiFi measurement study conducted in Edinburgh, leveraging participants with mobile phones traveling on public transport buses. Our findings and contributions are as follows:

- WiFi spectrum usage is quite unevenly distributed across 2.4GHz and 5GHz unlicensed bands as well as among various channels within the 2.4GHz (section IV.A).
- Many WiFi access points (APs) contend on the same channel with around 10 other APs (and their clients) in the nearby vicinity, thereby potentially experience severe interference. This is a result of the common practice of uncoordinated and non-adaptive channel assignment to home WiFi routers which are often left to use preset factory configuration settings for channel etc. (section IV.B).
- We also look into the distribution of open APs, which could be leveraged for vehicular WiFi access [11].

This work was supported in part by a Cisco Research Award.
978-1-4799-0913-1/14/$31.00 © 2014 IEEE

[1]http://cellscope.berkeley.edu/
[2]http://web.media.mit.edu/~pamplona/NETRA/

Example: "Urban WiFi Characterization via Mobile Crowdsensing"

Analysis concerning the WiFi quality in cities.

Source: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6838233

(a)

	Min	Median	Mean	Max
Location Error (m)	4	8	9.6	1095

(b)

Total number of measurements (scans)	147488
Distinct measurement locations	11225
Distinct APs detected	13800
Distinct open access APs detected	2977

(c)

Fig. 1. (a) Mobile crowdsensing based WiFi AP scanning measurements shown as a heatmap; (b) Location error statistics for the collected measurement dataset; (c) Filtered measurement dataset summary.

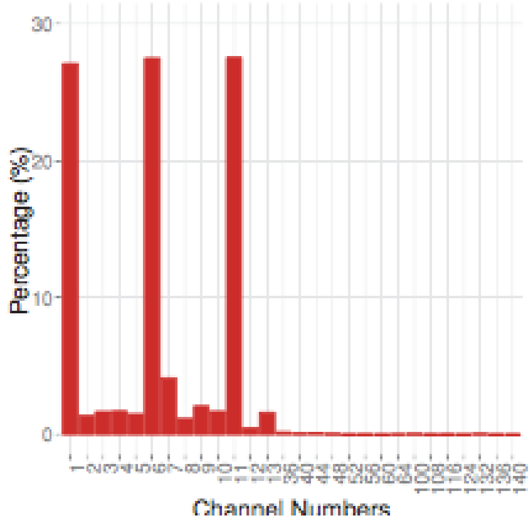


Fig. 2. Relative usage of different channels across 2.4GHz and 5GHz bands by the detected APs.

III. METHODOLOGY

Our mobile crowdsensing based urban WiFi characterization study is done using Android phones, specifically Samsung Galaxy S III [7] phones which feature a 802.11a/b/g/n radio that can operate in both 2.4GHz and 5GHz unlicensed bands. We rely solely on passive scanning based measurement, listening to AP beacons. The information available at the user level with the Android API for passive scans is limited to: SSID, BSSID, channel, RSSI and the security scheme in use. For the measurements, we use the freely available RF Signal Tracker app [24], which keeps passively scanning for WiFi access points (APs) in the background every three seconds or on passing 5 meters; it locally stores the result of each scan tagged with GPS location and timestamp on the phone in a CSV file. As this app does not log location errors and is not open source, we have a developed an auxiliary app that runs alongside and records location errors. Measurement data from phones is subsequently transferred to a back-end server where custom python scripts are used to import the data into a database, which then is used for further querying, analysis and mapping of data.

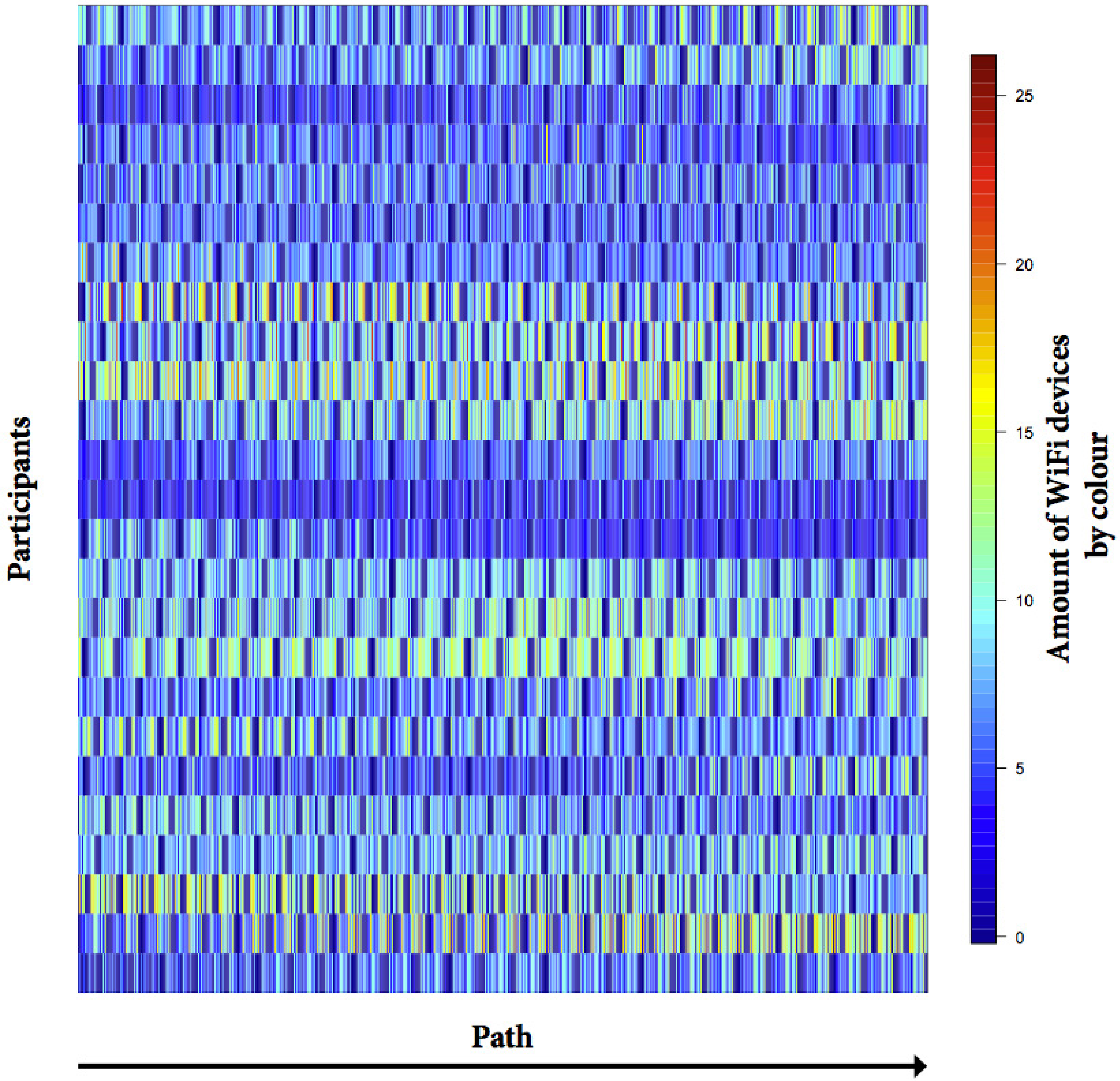
As mentioned at the outset, our urban WiFi characterization focuses on the city of Edinburgh, which is a typical European city [25] — smaller in size and densely populated, especially in the center. For proof-of-concept and wider spatial coverage with fewer participants in a short measurement period, we focus on a measurement scenario where participants are traveling on public transport vehicles. Specifically, our measurement results are obtained from phones carried by participants during the times they travel at low to moderate speeds on buses in the city operated by a local bus company called Lothian Buses [26]. In this sense, it follows a participatory sensing approach along the lines of earlier urban air/noise pollution monitoring studies [5], [6]. Measurements reported in this paper correspond to traveling over 31 buses over a 15 hour period in total. Note that in principle crowdsourcing based measurement can be done in a fully opportunistic manner, covering all modes of movement including walking, standing, etc. The limits we place are for above mentioned reasons. Also note that there is an assumption underlying our study that visible APs from next-door neighbors can also be seen from the street and vice versa.

Fig. 1(a) shows the total set of measurements as a heatmap. Red areas in the map indicate places where there is a high density of APs as well as those places with multiple measurements due to overlapping road segments between different bus routes. Fig. 1(b) lists the location error statistics across all measurements in our dataset. We observe that while the maximum error can be over 1Km reflecting locations that do not get a GPS fix, the error is under 50m in 95% of the cases. To obtain reliable spatial distribution of APs on the map, we filtered out the 5% of the measurements with location errors greater than 50m. Fig. 1(c) presents a summary of the resultant dataset. From closer inspection, we observe that majority of the APs correspond to home WiFi networks interspersed with the rest (e.g., WiFi hotspots).

IV. RESULTS

A. *Spectrum Usage*

We begin by looking at the channel usage of WiFi APs in our dataset. Fig. 2 shows the relative usage of different channels across 2.4GHz and 5GHz bands. Clearly, the channel

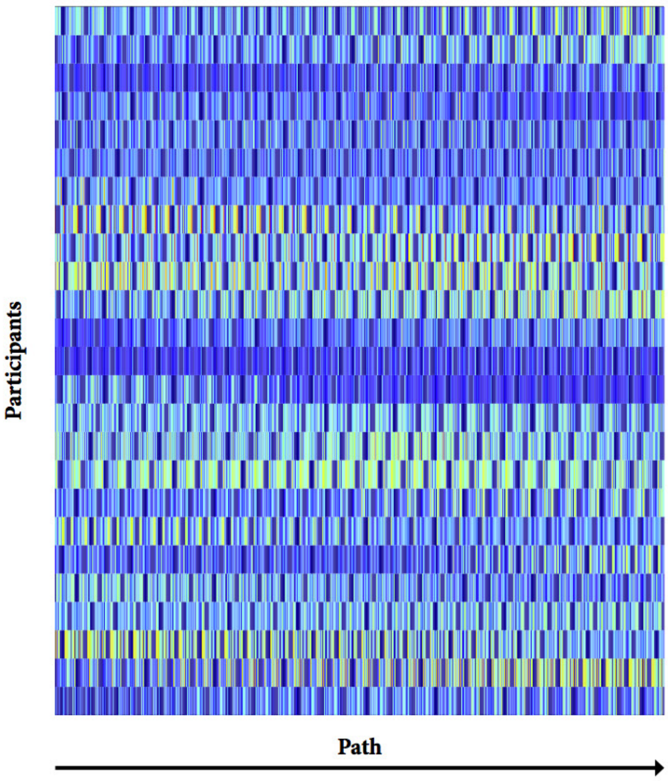

Participants
Path
Amount of WiFi devices by colour
25
20
15
10
5
0

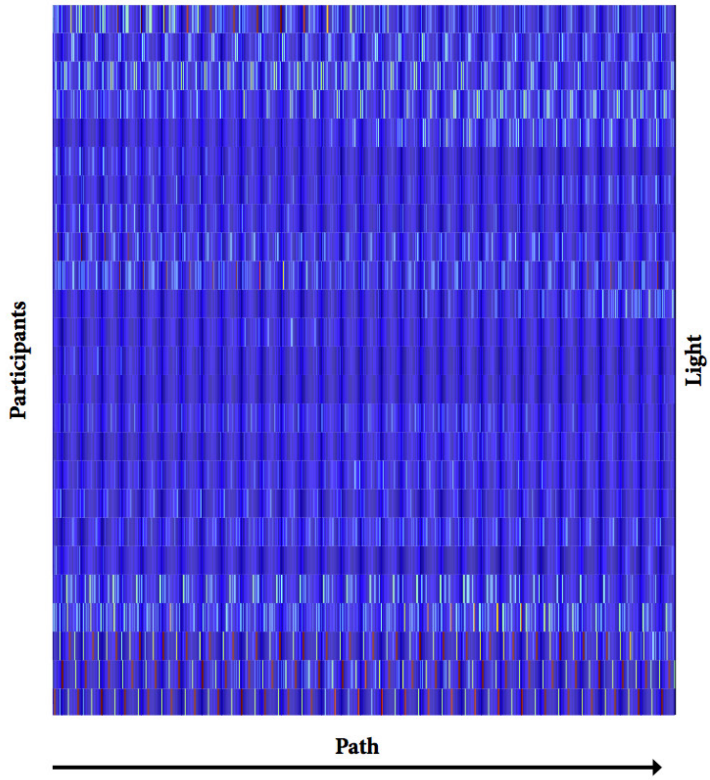
Backpack data heatmap

There seem to be days with fewer people on the streets.

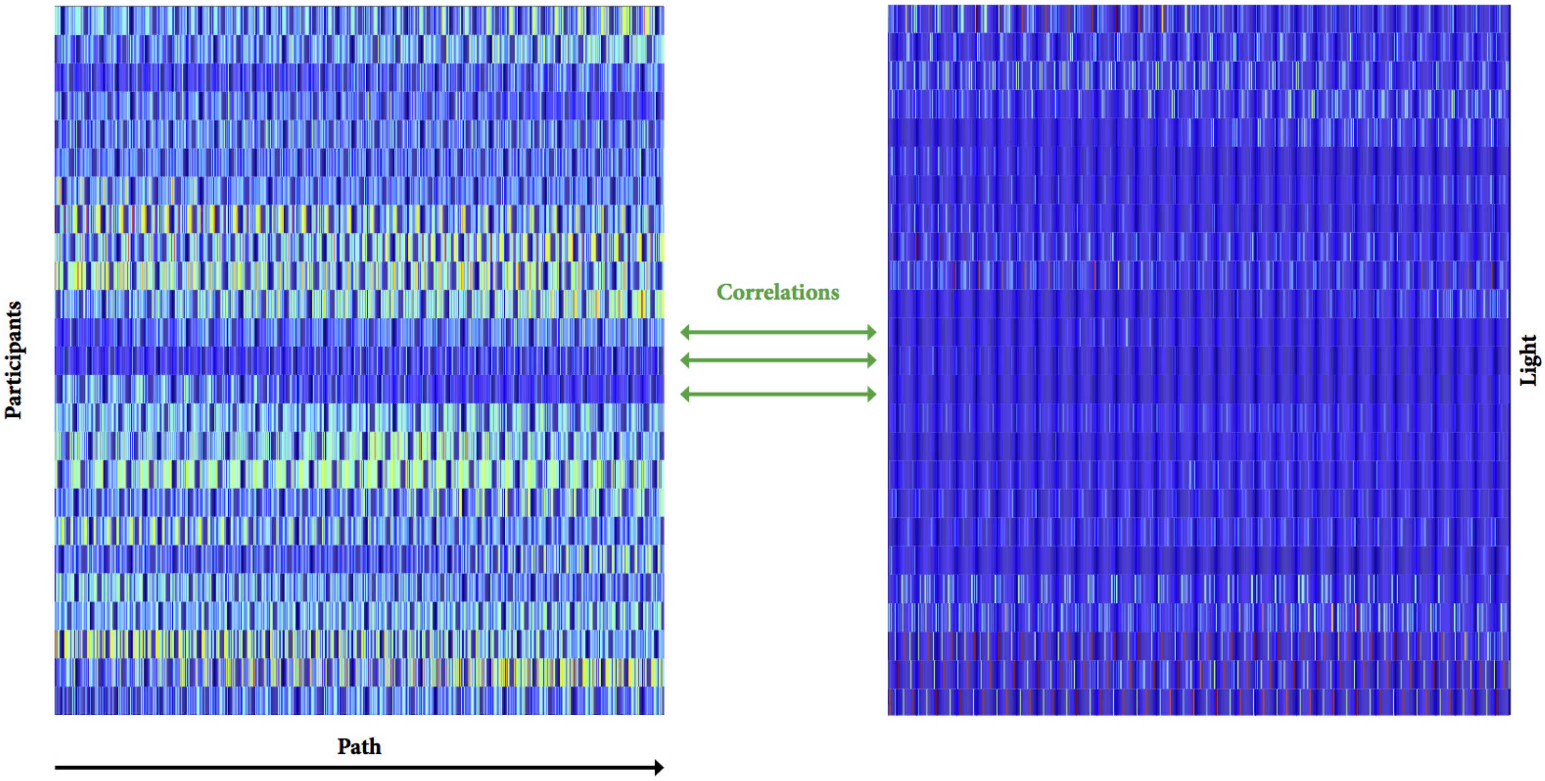
Assumption: Bad weather is responsible for this.

Question: Is there a link between the weather and the amount of people in the streets?

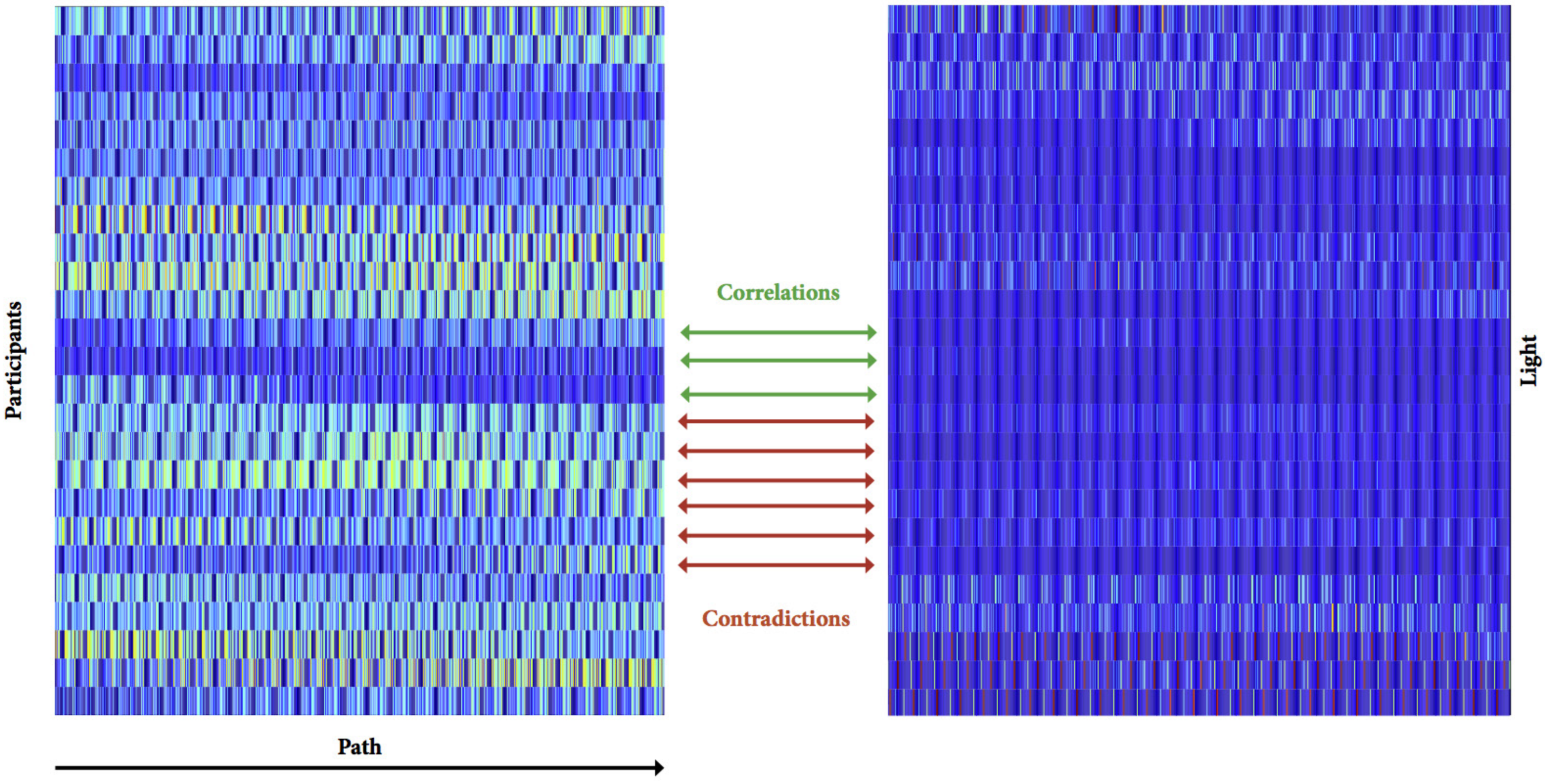




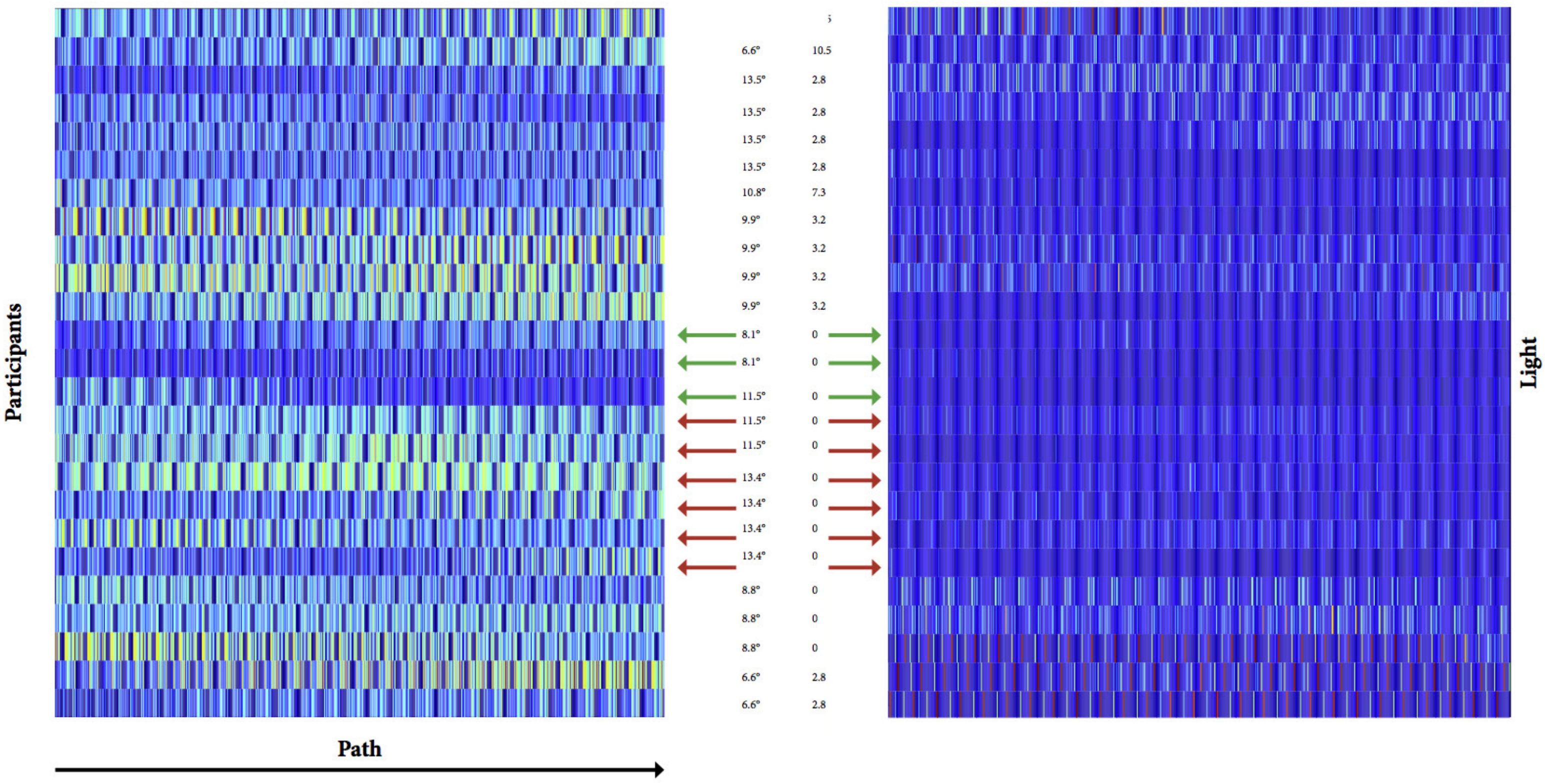
Comparison with light sensor data.
Green colour displays direct sunlight. Exclusively blue lines are cloudy days.



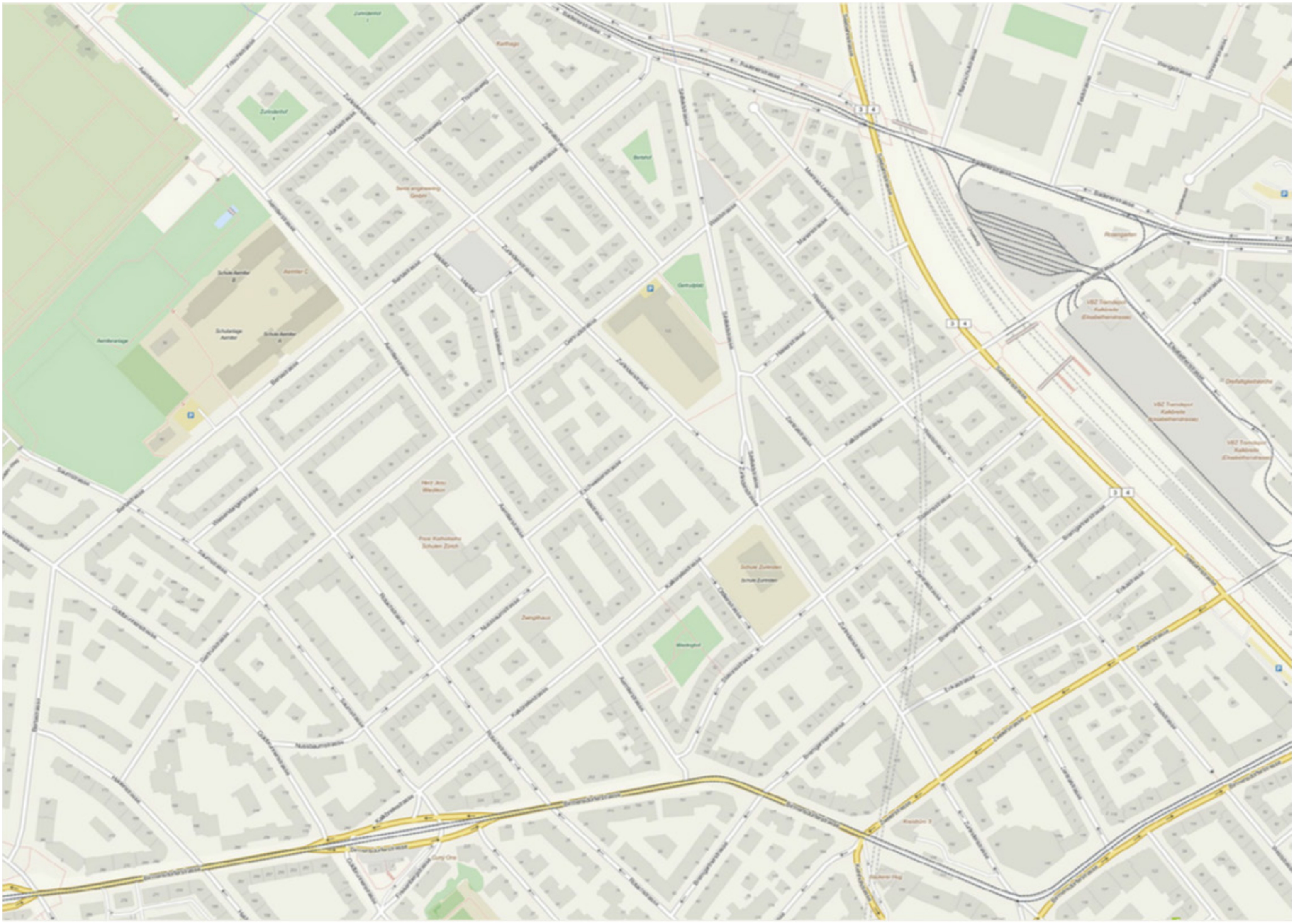
Searching for obvious correlations
If there is no sunshine over the timespan of three participants and obviously fewer people on the street.



Contradictions
There are some contradictionary days, where there is no sun but still many people on the street.



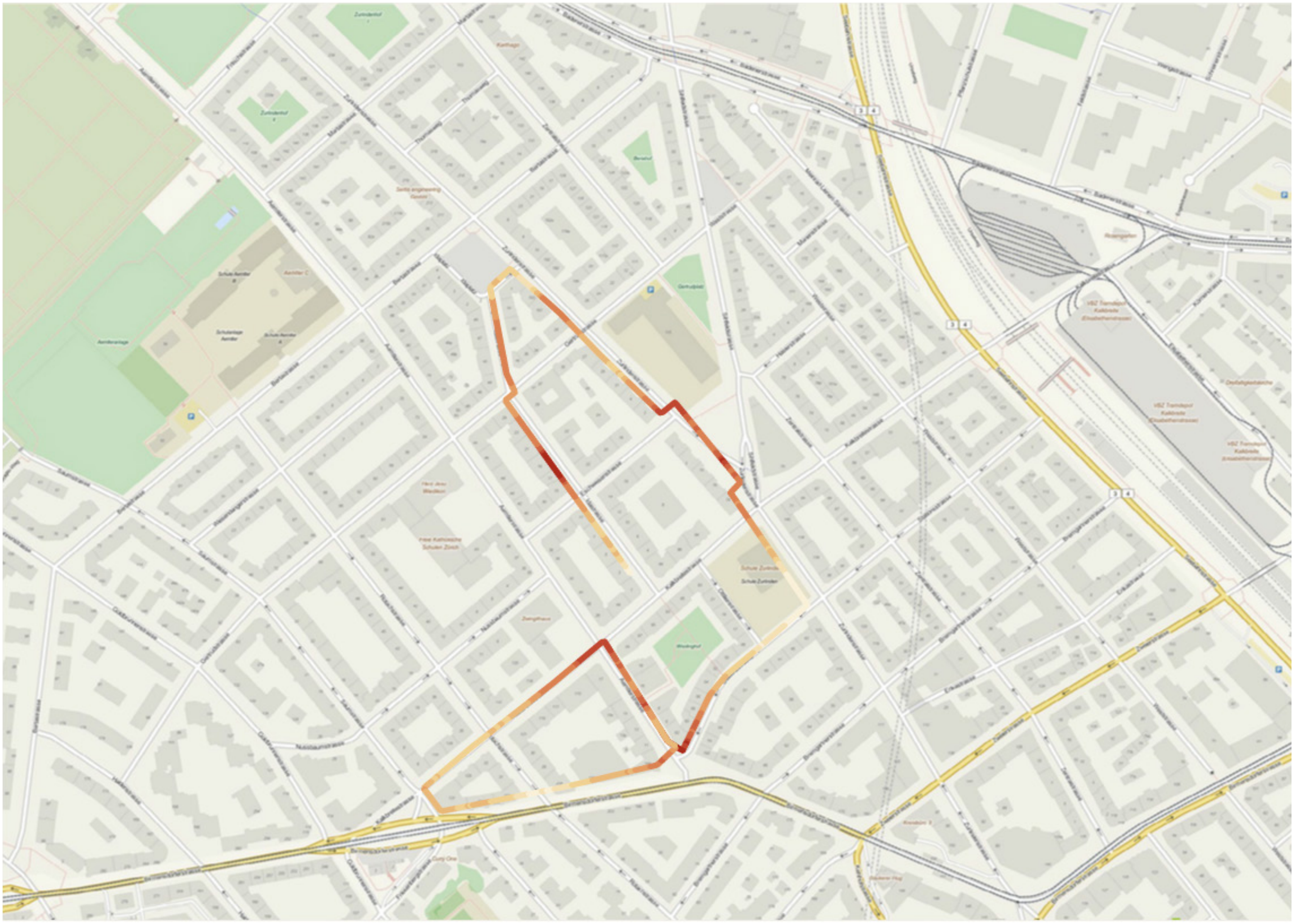
The contradictions could be explained by looking at the average temperature on those days



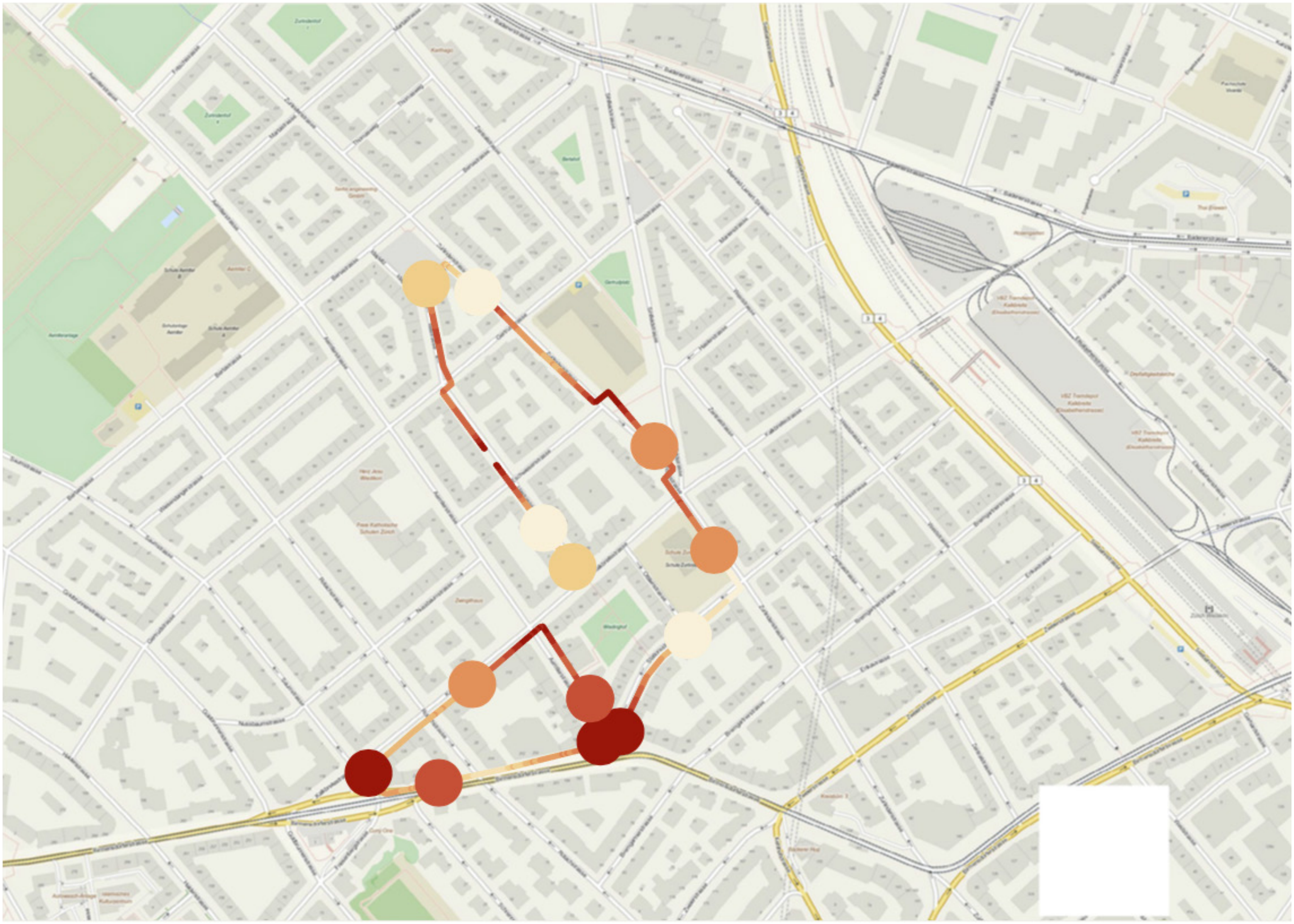
QGIS

Question: Is it possible to monitor the amount of people in the streets via QGIS?

Raw data input
Representing all the participants WiFi sniffer data on one map



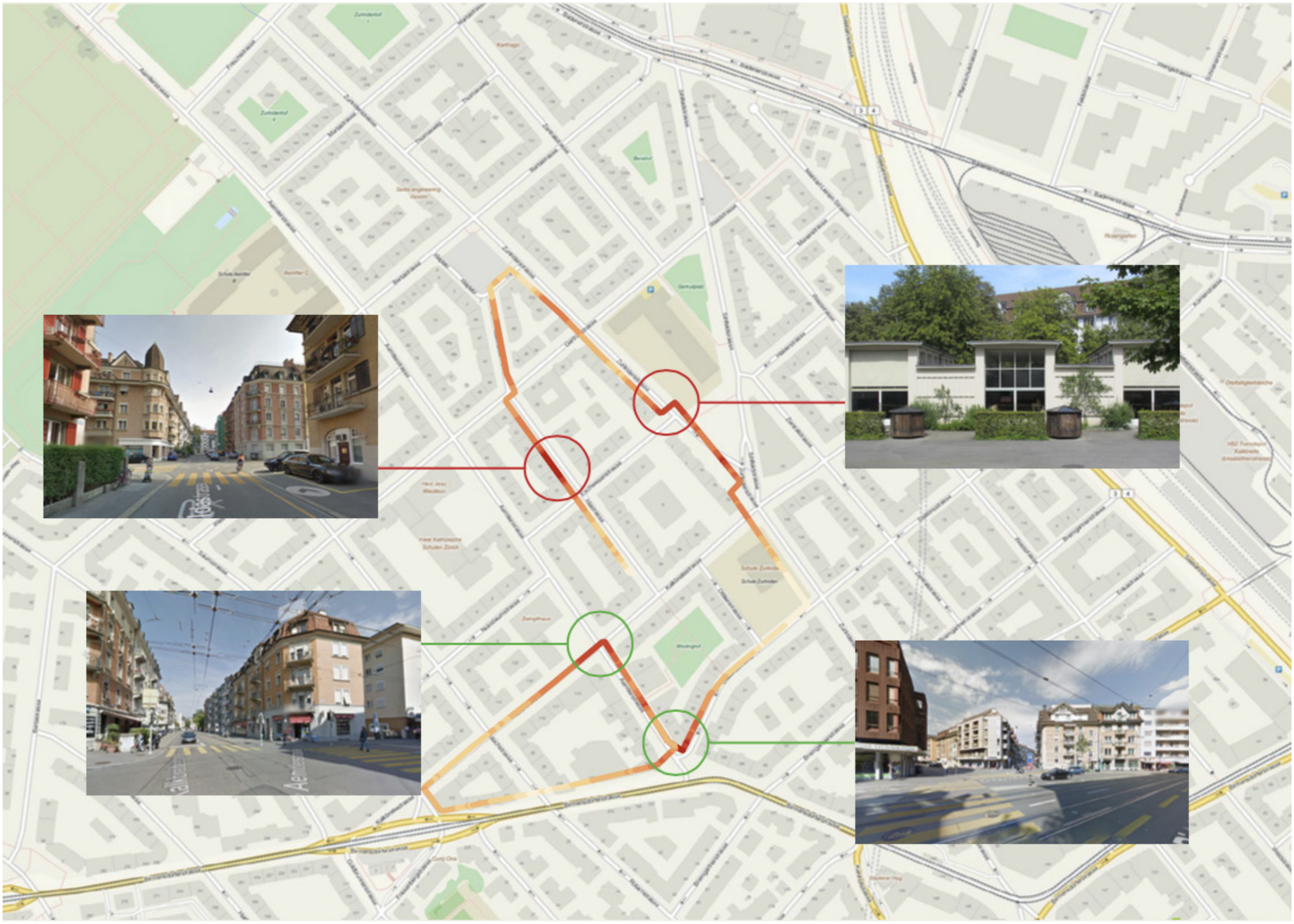
Average values for better display. Creating a standard path with the average data of all participants. There seem to be some areas with more people on the streets



Survey data
The surveys that were taken along the path show some deviations from the WiFi data.

Site impressions

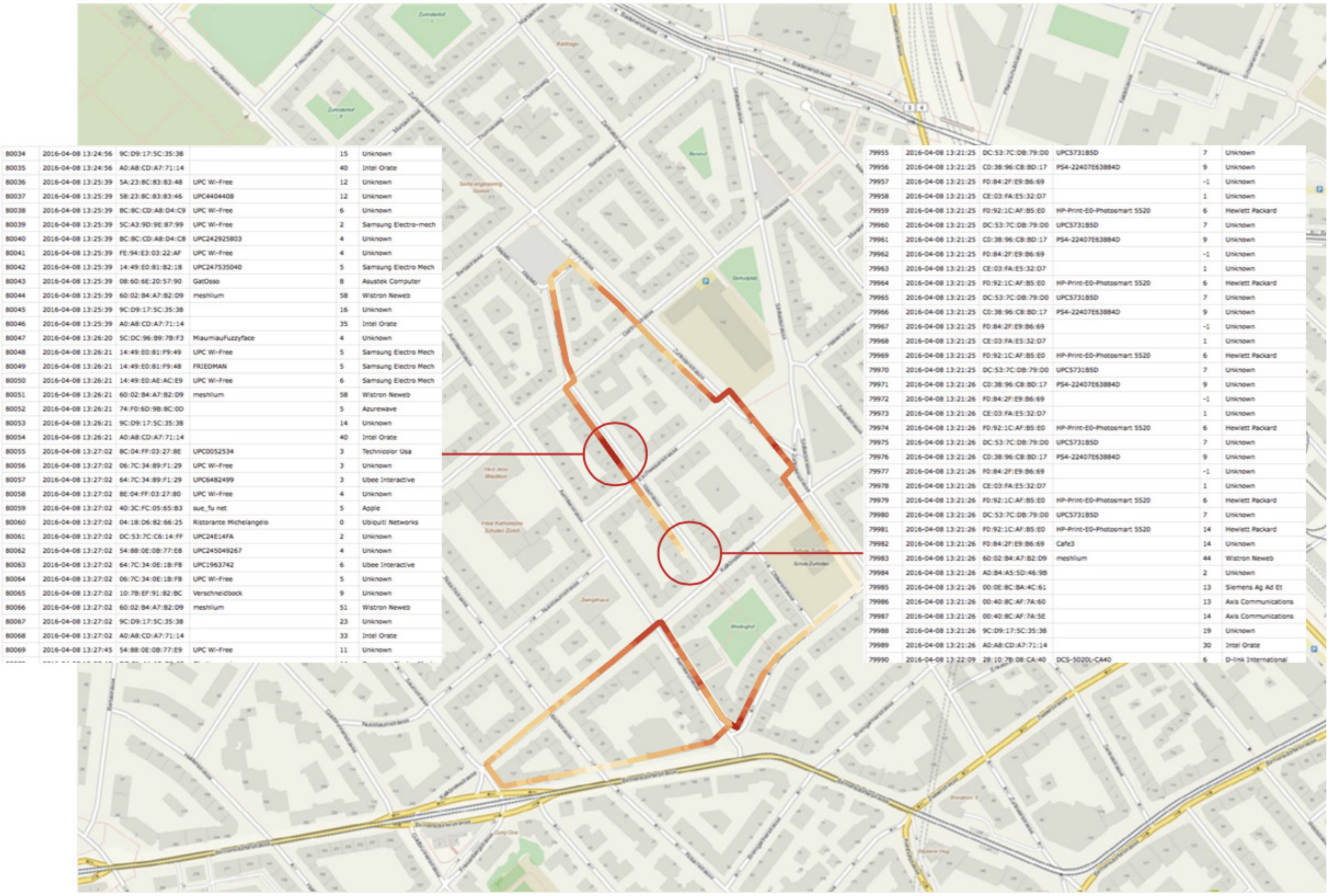
Two points seemed likely to be crowded ones. Cafes and pedestrians on the streets



Site impressions
The two others seemed to be rather empty.

Stationary devices?

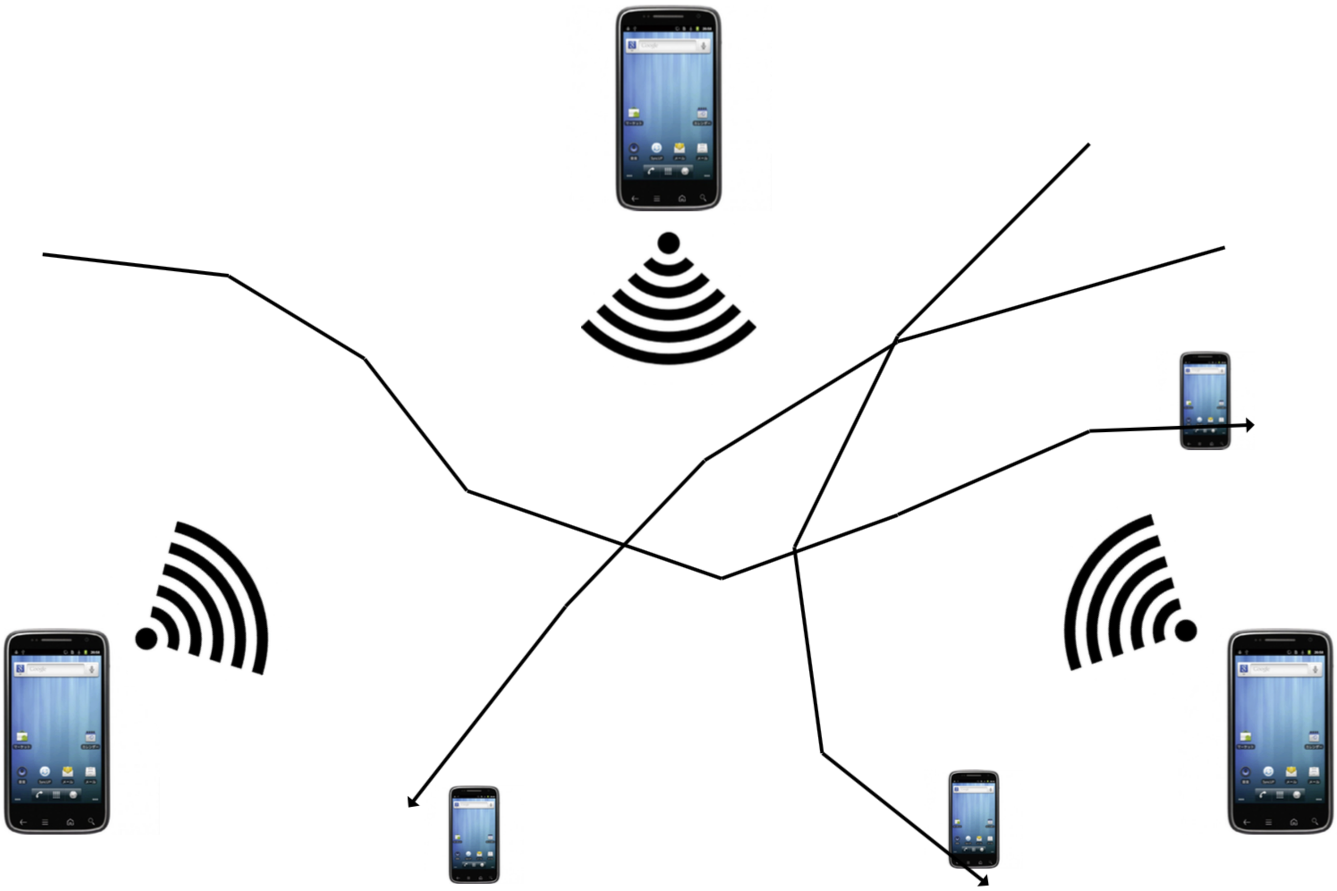
Possible Reason:
Code contains also stationary devices and for some reason there are many of them.



80034	2016-04-08 13:24:56	9C:D9:17:5C:35:38		15	Unknown
80035	2016-04-08 13:24:56	A0:A8:CD:A7:71:14		40	Intel Orate
80036	2016-04-08 13:25:39	5A:23:8C:83:83:48	UPC Wi-Free	12	Unknown
80037	2016-04-08 13:25:39	58:23:8C:83:83:46	UPC4404408	12	Unknown
80038	2016-04-08 13:25:39	BC:8C:CD:A8:D4:C9	UPC Wi-Free	6	Unknown
80039	2016-04-08 13:25:39	5C:A3:9D:9E:87:99	UPC Wi-Free	2	Samsung Electro-mech
80040	2016-04-08 13:25:39	BC:8C:CD:A8:D4:C8	UPC242925803	4	Unknown
80041	2016-04-08 13:25:39	FE:94:E3:03:22:AF	UPC Wi-Free	4	Unknown
80042	2016-04-08 13:25:39	14:49:E0:81:B2:18	UPC247535040	5	Samsung Electro Mech
80043	2016-04-08 13:25:39	08:60:6E:20:57:90	GatOsso	8	Asustek Computer
80044	2016-04-08 13:25:39	60:02:B4:A7:B2:D9	meshlium	58	Wistron Neweb
80045	2016-04-08 13:25:39	9C:D9:17:5C:35:38		16	Unknown
80046	2016-04-08 13:25:39	A0:A8:CD:A7:71:14		35	Intel Orate
80047	2016-04-08 13:26:20	5C:DC:96:B9:7B:F3	MiaumiauFuzzyface	4	Unknown
80048	2016-04-08 13:26:21	14:49:E0:81:F9:49	UPC Wi-Free	5	Samsung Electro Mech
80049	2016-04-08 13:26:21	14:49:E0:81:F9:48	FRIEDMAN	5	Samsung Electro Mech
80050	2016-04-08 13:26:21	14:49:E0:AE:AC:E9	UPC Wi-Free	6	Samsung Electro Mech
80051	2016-04-08 13:26:21	60:02:B4:A7:B2:D9	meshlium	58	Wistron Neweb
80052	2016-04-08 13:26:21	74:F0:6D:9B:8C:0D		5	Azurewave
80053	2016-04-08 13:26:21	9C:D9:17:5C:35:38		14	Unknown
80054	2016-04-08 13:26:21	A0:A8:CD:A7:71:14		40	Intel Orate
80055	2016-04-08 13:27:02	8C:04:FF:03:27:8E	UPC0052534	3	Technicolor Usa
80056	2016-04-08 13:27:02	06:7C:34:89:F1:29	UPC Wi-Free	3	Unknown
80057	2016-04-08 13:27:02	64:7C:34:89:F1:29	UPC6482499	3	Ubee Interactive
80058	2016-04-08 13:27:02	8E:04:FF:03:27:80	UPC Wi-Free	4	Unknown
80059	2016-04-08 13:27:02	40:3C:FC:05:65:B3	sue_fu net	5	Apple
80060	2016-04-08 13:27:02	04:18:D6:82:66:25	Ristorante Michelangelo	0	Ubiquiti Networks
80061	2016-04-08 13:27:02	DC:53:7C:C6:14:FF	UPC24E14FA	2	Unknown
80062	2016-04-08 13:27:02	54:88:0E:0B:77:E8	UPC245049267	4	Unknown
80063	2016-04-08 13:27:02	64:7C:34:0E:1B:F8	UPC1963742	6	Ubee Interactive
80064	2016-04-08 13:27:02	06:7C:34:0E:1B:F8	UPC Wi-Free	5	Unknown
80065	2016-04-08 13:27:02	10:7B:EF:91:82:BC	Verschneidbock	9	Unknown
80066	2016-04-08 13:27:02	60:02:B4:A7:B2:D9	meshlium	51	Wistron Neweb
80067	2016-04-08 13:27:02	9C:D9:17:5C:35:38		23	Unknown
80068	2016-04-08 13:27:02	A0:A8:CD:A7:71:14		33	Intel Orate
80069	2016-04-08 13:27:45	54:88:0E:0B:77:E9	UPC Wi-Free	11	Unknown

79955	2016-04-08 13:21:25	DC:53:7C:DB:79:D0	UPC5731B5D	7	Unknown
79956	2016-04-08 13:21:25	C0:38:96:C8:BD:17	PS4-22407E63884D	9	Unknown
79957	2016-04-08 13:21:25	F0:B4:2F:E9:B6:69		-1	Unknown
79958	2016-04-08 13:21:25	CE:03:FA:E5:32:D7		1	Unknown
79959	2016-04-08 13:21:25	F0:92:1C:AF:B5:E0	HP-Print-E0-Photosmart 5520	6	Hewlett Packard
79960	2016-04-08 13:21:25	DC:53:7C:DB:79:D0	UPC5731B5D	7	Unknown
79961	2016-04-08 13:21:25	C0:38:96:C8:BD:17	PS4-22407E63884D	9	Unknown
79962	2016-04-08 13:21:25	F0:B4:2F:E9:B6:69		-1	Unknown
79963	2016-04-08 13:21:25	CE:03:FA:E5:32:D7		1	Unknown
79964	2016-04-08 13:21:25	F0:92:1C:AF:B5:E0	HP-Print-E0-Photosmart 5520	6	Hewlett Packard
79965	2016-04-08 13:21:25	DC:53:7C:DB:79:D0	UPC5731B5D	7	Unknown
79966	2016-04-08 13:21:25	C0:38:96:C8:BD:17	PS4-22407E63884D	9	Unknown
79967	2016-04-08 13:21:25	F0:B4:2F:E9:B6:69		-1	Unknown
79968	2016-04-08 13:21:25	CE:03:FA:E5:32:D7		1	Unknown
79969	2016-04-08 13:21:25	F0:92:1C:AF:B5:E0	HP-Print-E0-Photosmart 5520	6	Hewlett Packard
79970	2016-04-08 13:21:25	DC:53:7C:DB:79:D0	UPC5731B5D	7	Unknown
79971	2016-04-08 13:21:26	C0:38:96:C8:BD:17	PS4-22407E63884D	9	Unknown
79972	2016-04-08 13:21:26	F0:B4:2F:E9:B6:69		-1	Unknown
79973	2016-04-08 13:21:26	CE:03:FA:E5:32:D7		1	Unknown
79974	2016-04-08 13:21:26	F0:92:1C:AF:B5:E0	HP-Print-E0-Photosmart 5520	6	Hewlett Packard
79975	2016-04-08 13:21:26	DC:53:7C:DB:79:D0	UPC5731B5D	7	Unknown
79976	2016-04-08 13:21:26	C0:38:96:C8:BD:17	PS4-22407E63884D	9	Unknown
79977	2016-04-08 13:21:26	F0:B4:2F:E9:B6:69		-1	Unknown
79978	2016-04-08 13:21:26	CE:03:FA:E5:32:D7		1	Unknown
79979	2016-04-08 13:21:26	F0:92:1C:AF:B5:E0	HP-Print-E0-Photosmart 5520	6	Hewlett Packard
79980	2016-04-08 13:21:26	DC:53:7C:DB:79:D0	UPC5731B5D	7	Unknown
79981	2016-04-08 13:21:26	F0:92:1C:AF:B5:E0	HP-Print-E0-Photosmart 5520	14	Hewlett Packard
79982	2016-04-08 13:21:26	F0:B4:2F:E9:B6:69	Cafe3	14	Unknown
79983	2016-04-08 13:21:26	60:02:B4:A7:B2:D9	meshlium	44	Wistron Neweb
79984	2016-04-08 13:21:26	A0:B4:A5:5D:46:9B		2	Unknown
79985	2016-04-08 13:21:26	00:0E:8C:BA:4C:61		13	Siemens Ag Ad Et
79986	2016-04-08 13:21:26	00:40:8C:AF:7A:60		13	Axis Communications
79987	2016-04-08 13:21:26	00:40:8C:AF:7A:5E		14	Axis Communications
79988	2016-04-08 13:21:26	9C:D9:17:5C:35:38		19	Unknown
79989	2016-04-08 13:21:26	A0:A8:CD:A7:71:14		30	Intel Orate
79990	2016-04-08 13:22:09	28:10:7B:08:CA:40	DCS-5020L-CA40	6	D-link International

Raw data
Raw data shows a large amount of stationary devices at mentioned point.



Triangulating
Is it possible to determine the exact position of people via WiFi tracking?

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