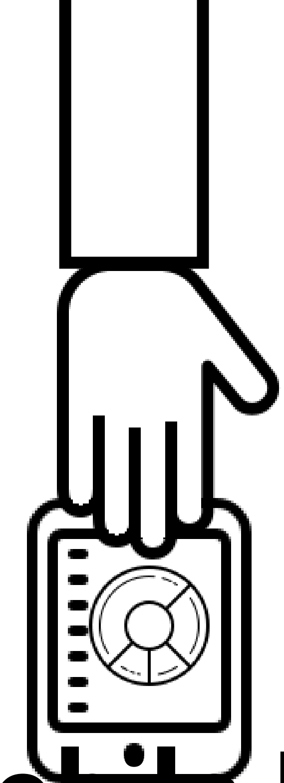
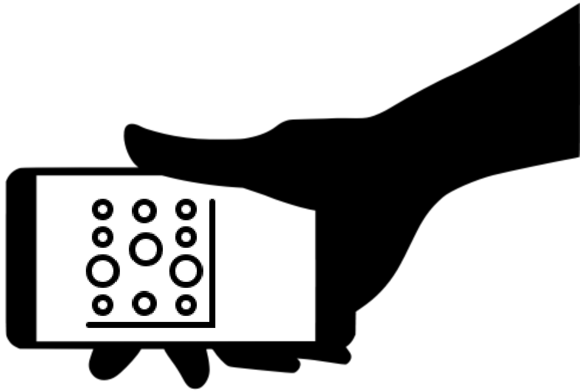
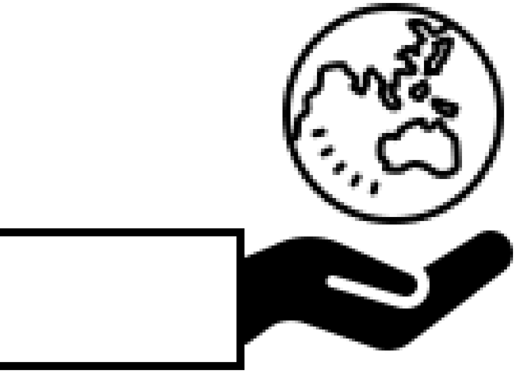
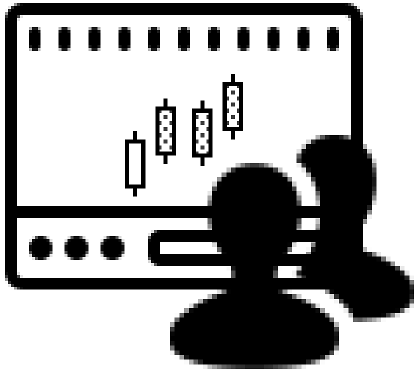




Visualization for Mobile Devices & Embedded Experiences

Petra Isenberg
@dr_pi petra.isenberg@inria.fr





Aviz Visual Analytics Project

Inria université PARIS-SACLAY

https://icons8.com/


VISUALIZATION
https://www.piqsels.com/

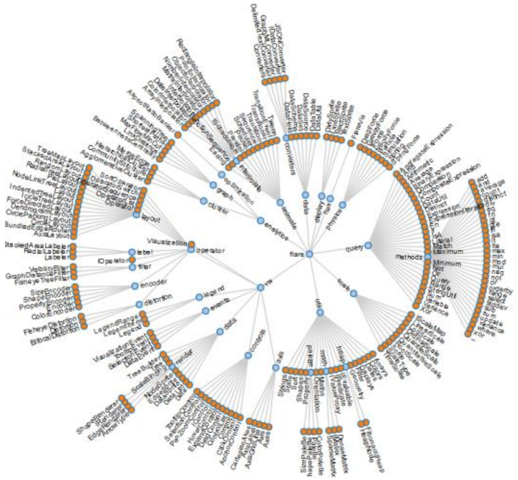
“CRITICAL THINKING WITH DATA”

(and sometimes enjoyment & reminiscence)

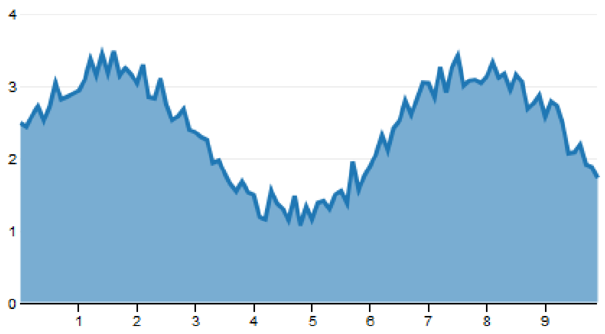
Why Visualization

- We are very good at recognizing visual patterns
- We need to see and understand in order to explain, reason, and make decisions

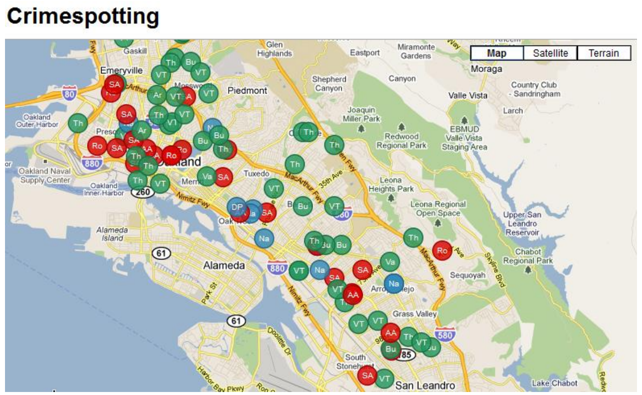
common examples



graphs / hierarchies



charts



maps

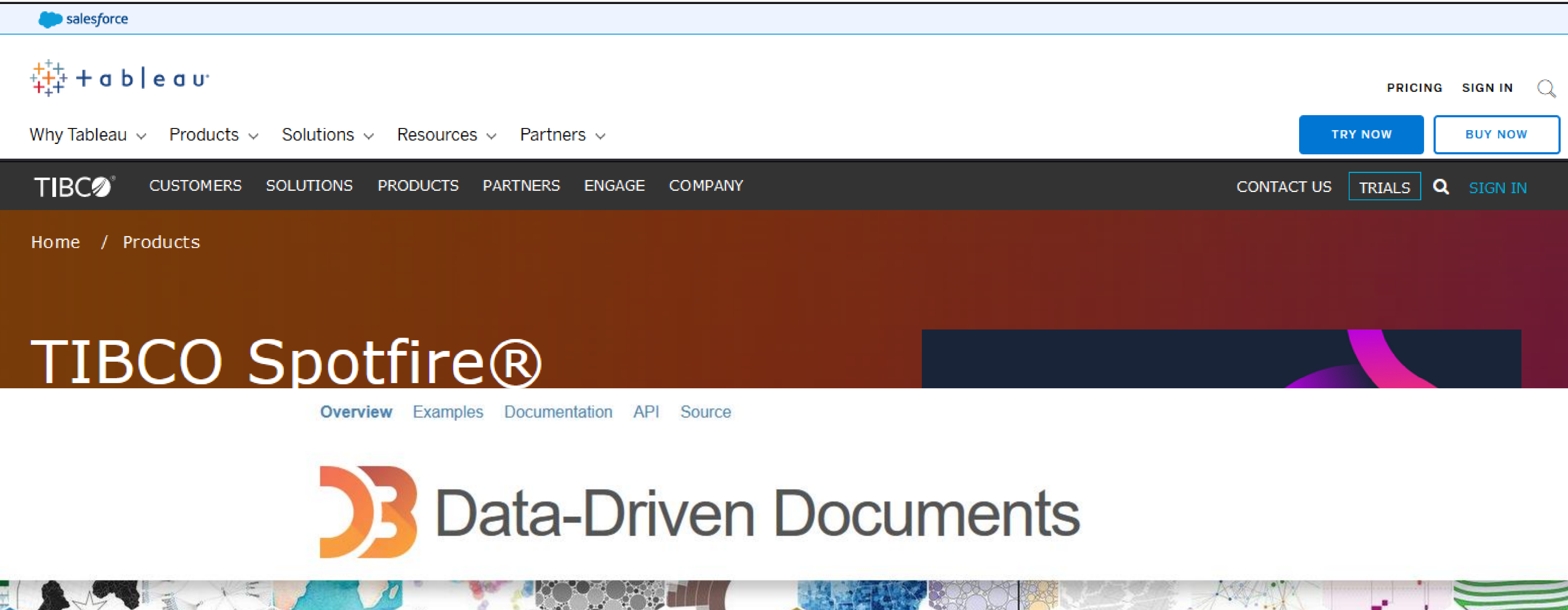
→ use of interactive computer-supported visual representations of data [Card et al.99]

RESEARCH CHALLENGES

in Visualization

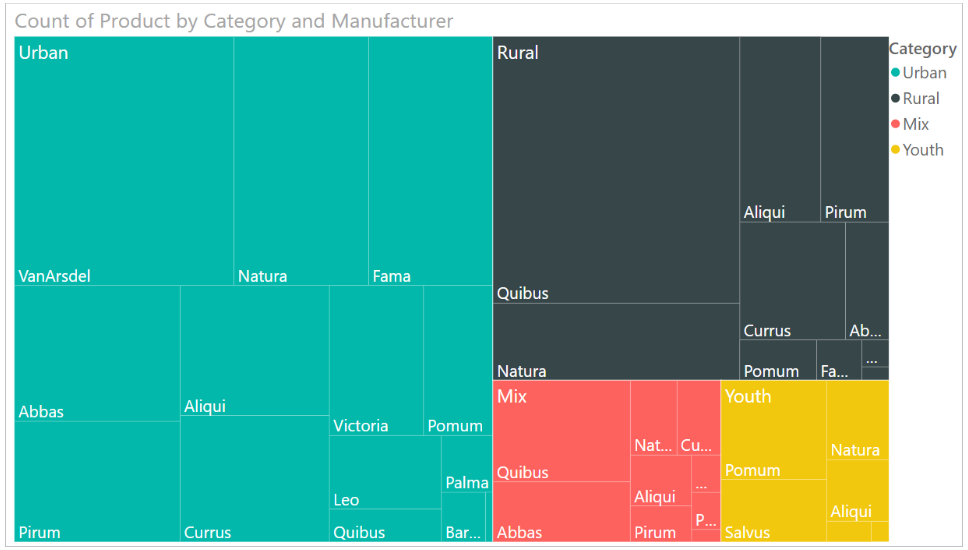
Visualization as a Research Field

- Tools for visualization creation

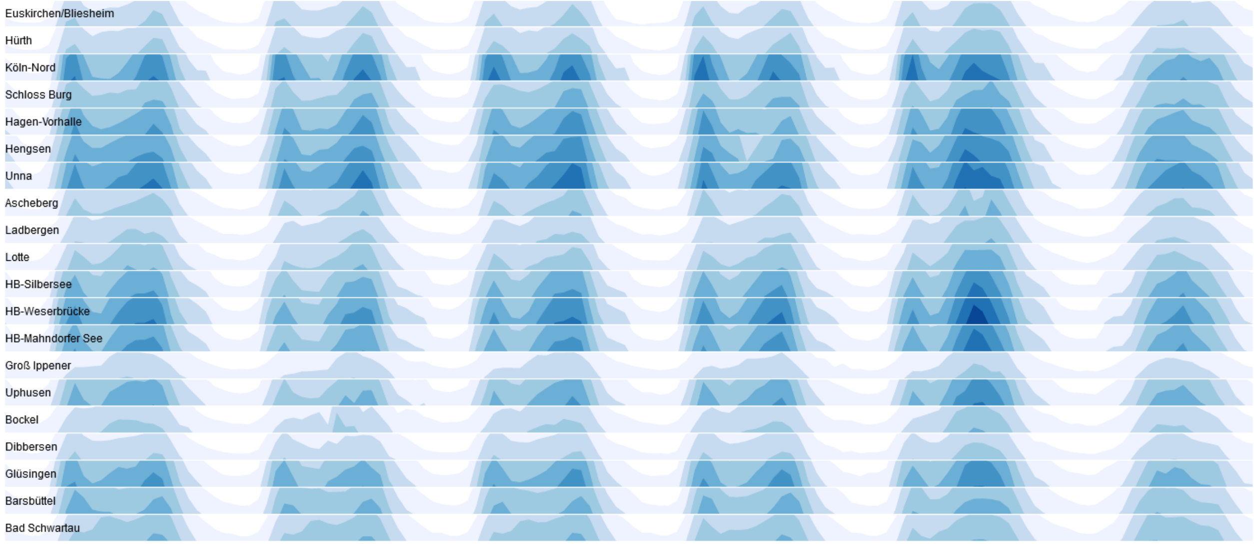


Visualization as a Research Field

- Tools for visualization creation
- New data encoding techniques



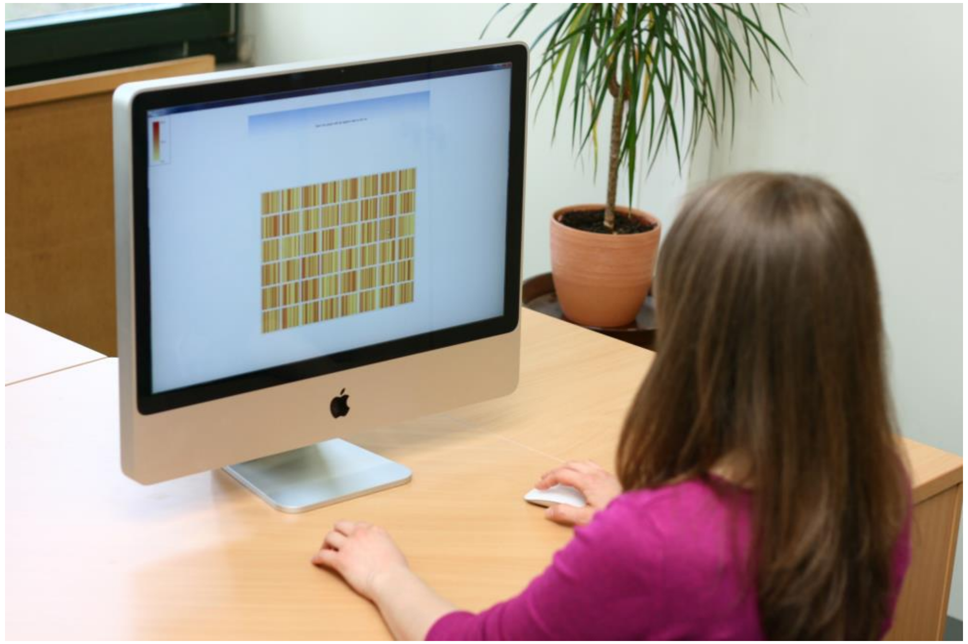
Treemap
ca. 1990/91



Horizon Charts
2005

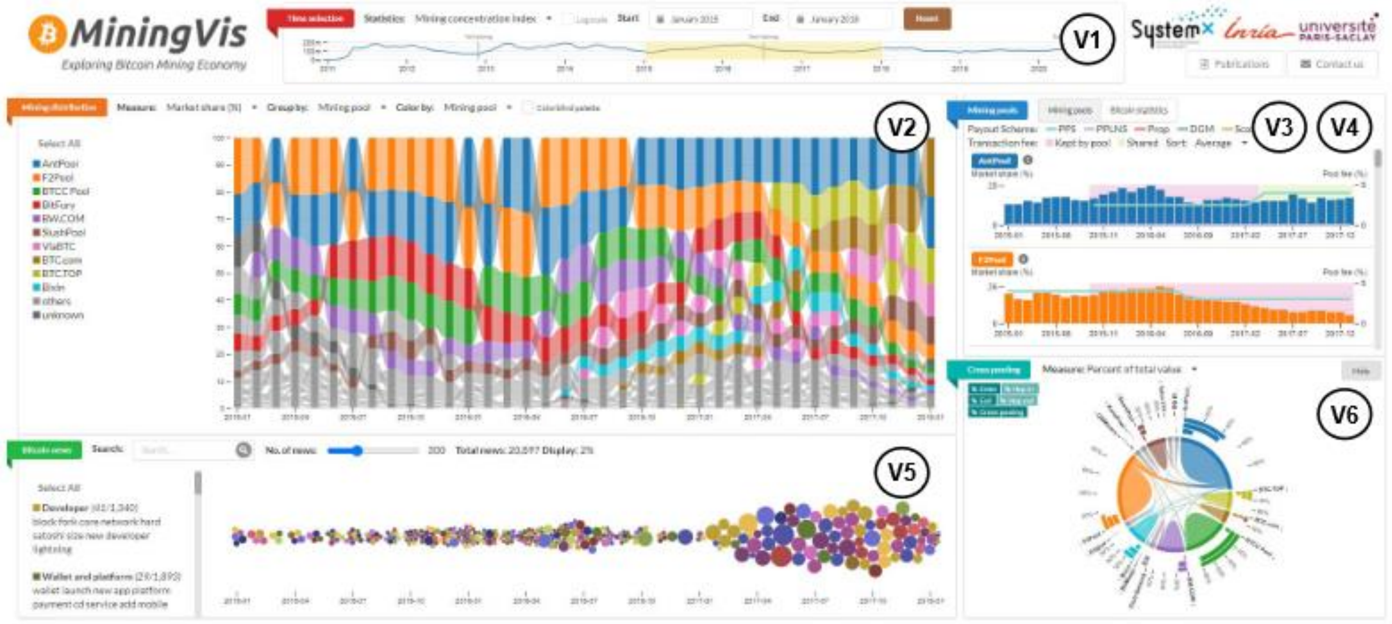
Visualization as a Research Field

- Tools for visualization creation
- New data encoding techniques
- **Generate empirical knowledge from user studies**



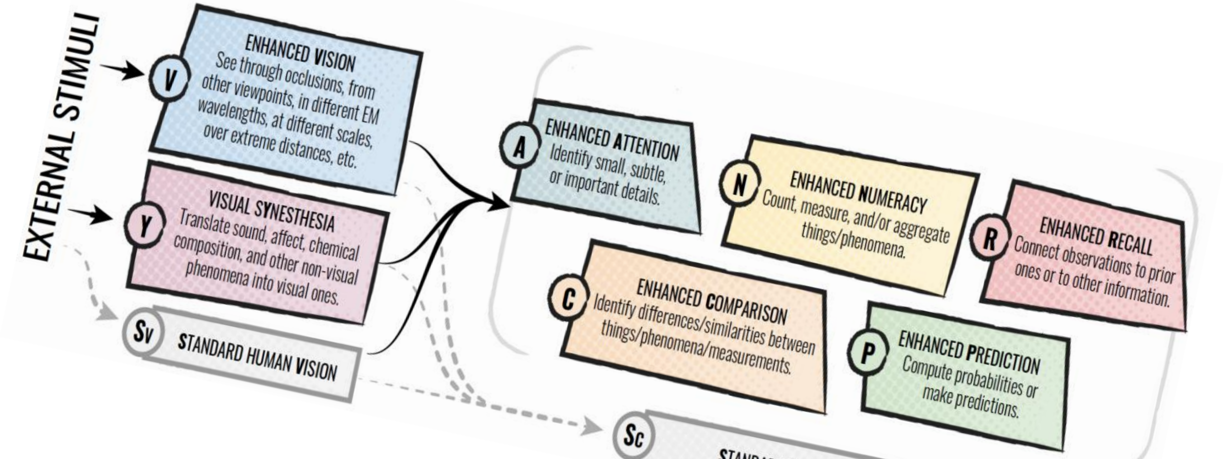
Visualization as a Research Field

- Tools for visualization creation
- New data encoding techniques
- **Generate empirical knowledge from user studies**
- Applications for visual analytics support



Visualization as a Research Field

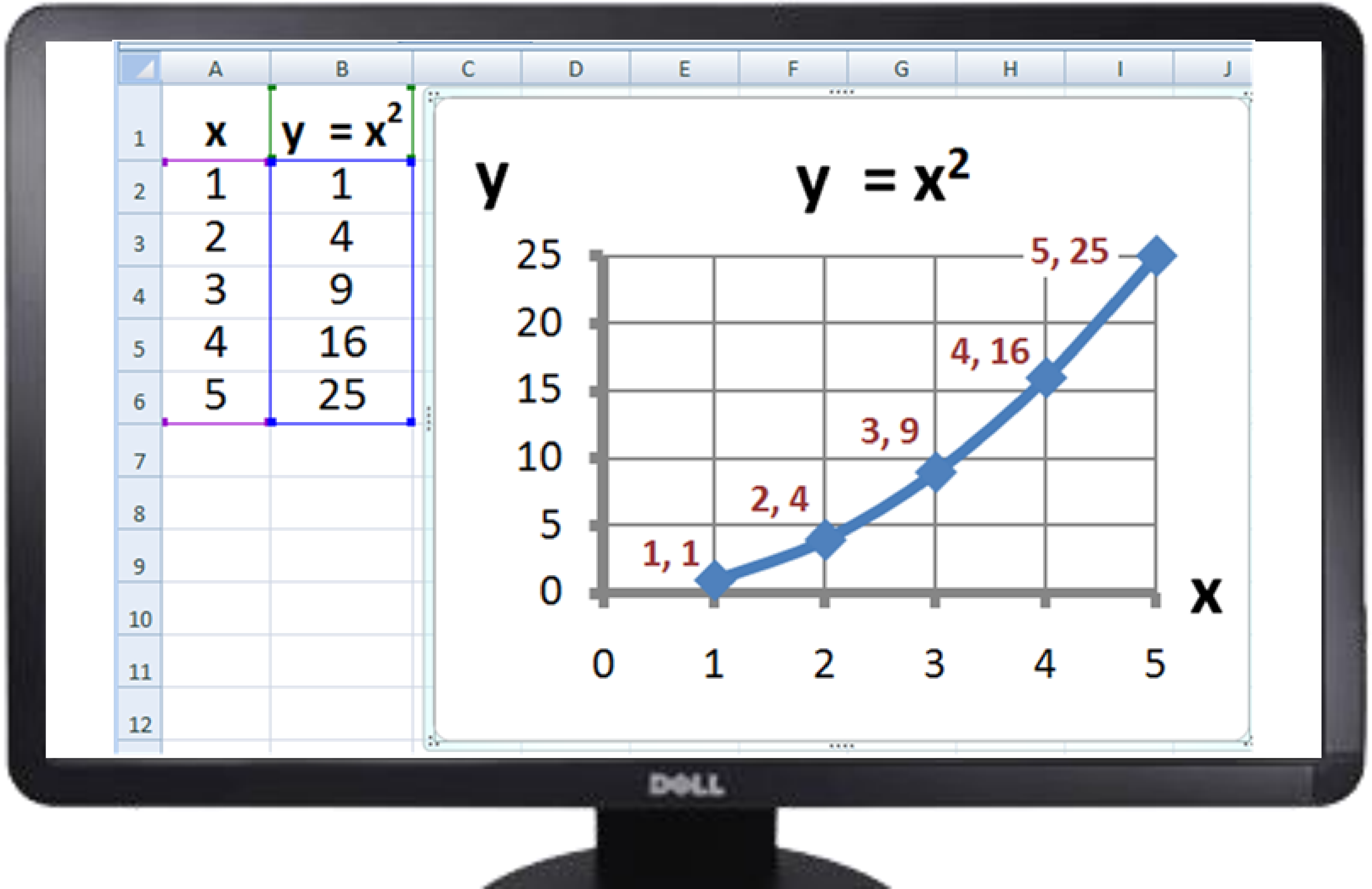
- Tools for visualization creation
- New data encoding techniques
- **Generate empirical knowledge from user studies**
- Applications for visual analytics support
- **Visualization frameworks, models, and theories**



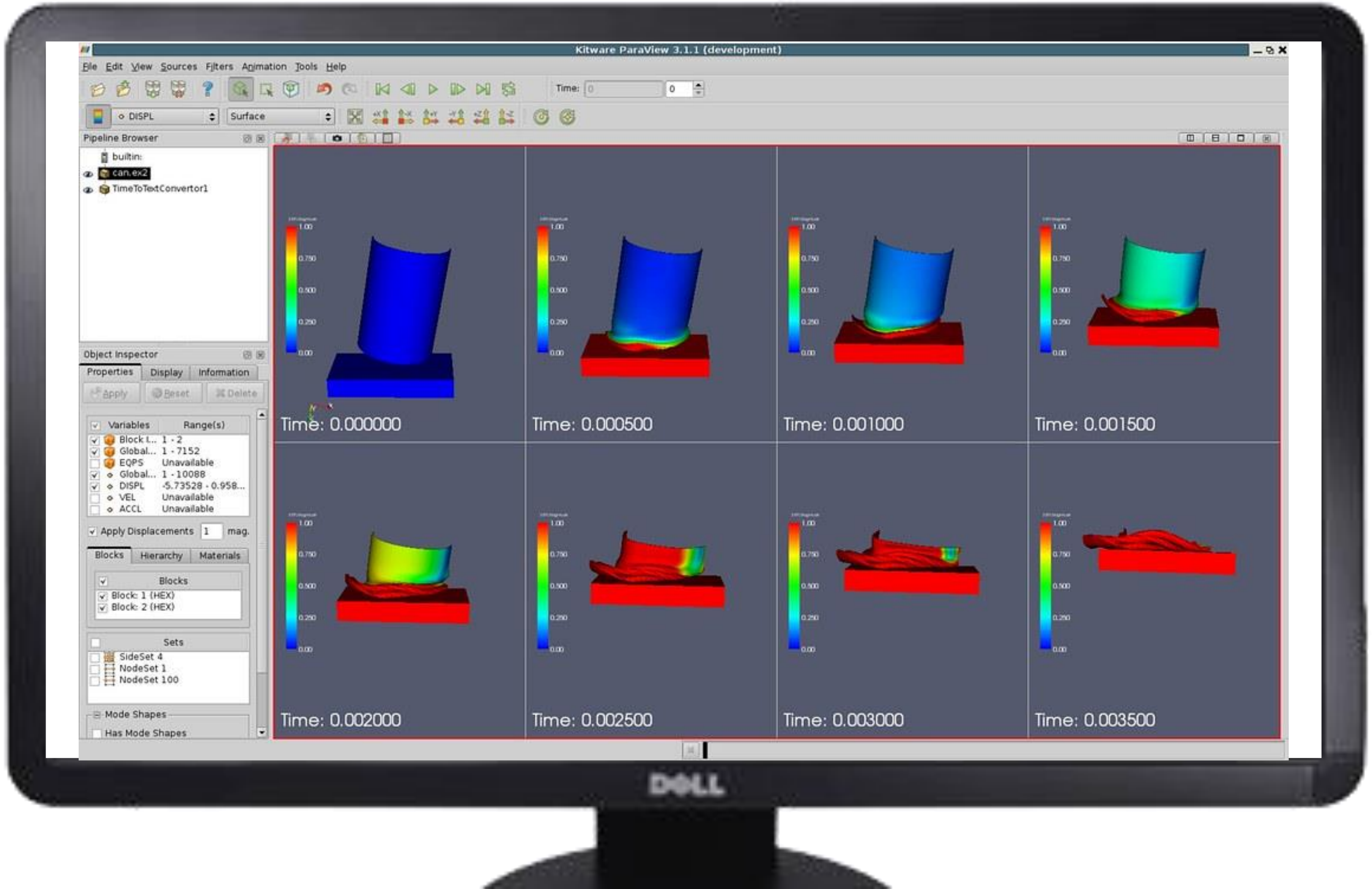
Most of VIS research

by Chris on Flickr

Data analysis software, simple statistics, …



Tools for experts…

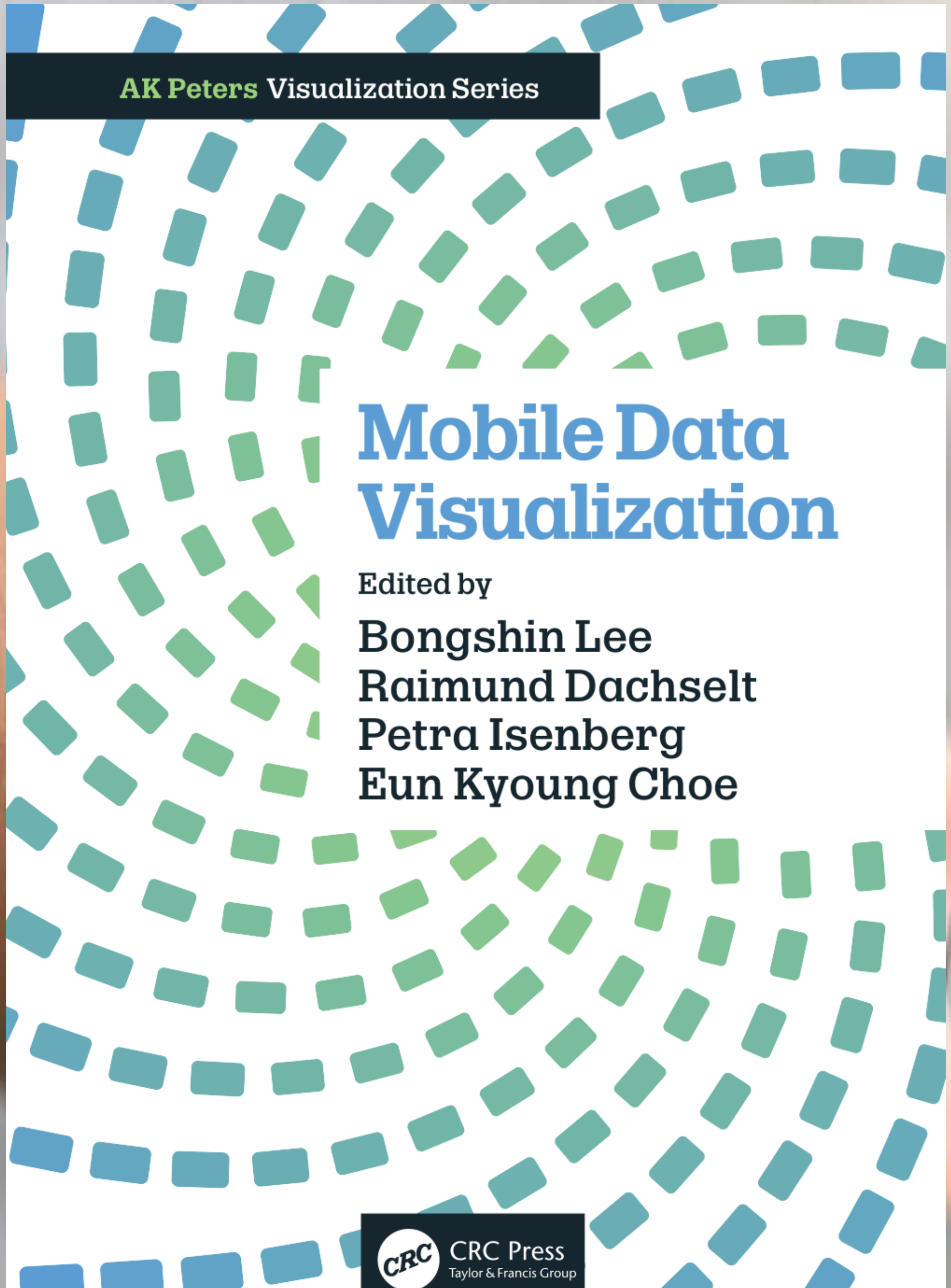


Positioning in the Visualization Community

Most work in community

My work


健身记录
3:38
锻炼 53%
16/30 分钟
站立 66%
8/12 小时
上午 12
6
下午 12
6


AK Peters Visualization Series
Mobile Data Visualization
Edited by
Bongshin Lee
Raimund Dachselt
Petra Isenberg
Eun Kyoung Choe
CRC Press
Taylor & Francis Group

Smartwatches

- Smartwatches are data dashboards
- Information design is based on no empirical foundations

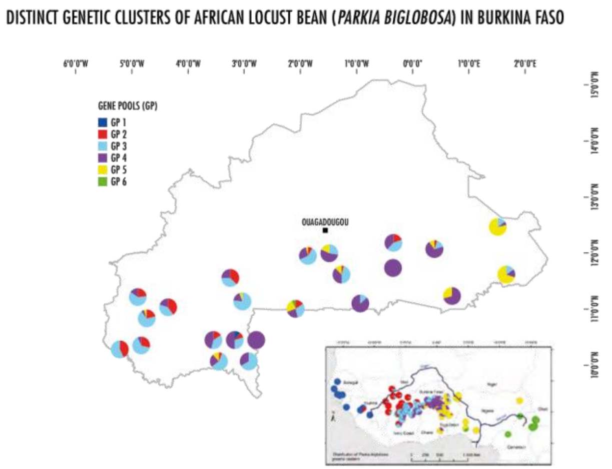
- Past research mostly about:
  - technical capabilities of smartwatches (sensors, batteries,…)
  - interaction techniques, or
  - their role in people’s life

NEW CHALLENGES

DISPLAY SPACE

MICRO VISUALIZATIONS

Design and Analysis of Visualizations for Small Display Spaces



The State of the World's Forests: Forests, Biodiversity and People
Authors: UN Environment Programme (UNEP), Food and Agriculture Organization of the United Nations (FAO)

Glucose is a ubiquitous fuel in biology. It is used as an energy source in organisms The current reading is  **glucose 6.6** for our patient Philippe. This reading means he is currently in serious trouble even though the readings are on a upwards trend. equat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

E.R.Tufte. Beautiful Evidence. GraphicsPress, Cheshire, CT. 2006.

WHAT ARE MICRO VISUALIZATIONS?

"micro visualizations are small-scale visualizations"

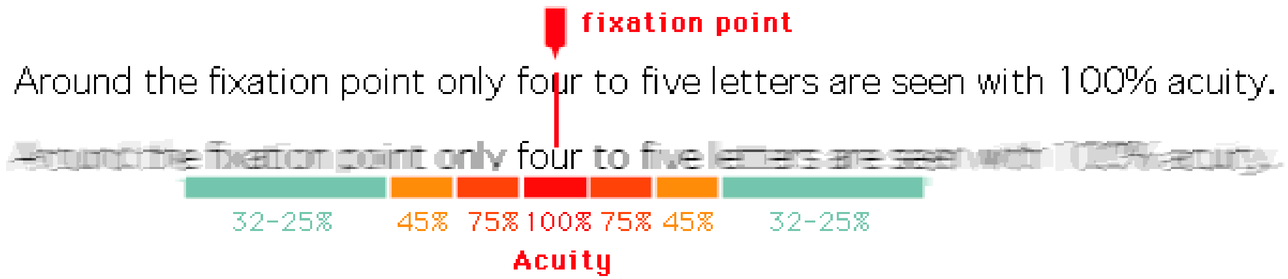
What is small?


1cm
Steps
3087
Km.
2.28
12:54
34
Kcal
1093
Bpm
94
76%
22-11
GARMIN
LIGHT
UP·MENU
DOWN
BACK·LAP


~10m x 7m

WHAT ARE MICRO VISUALIZATIONS?

“micro visualizations are small-scale visualizations that fit roughly into foveal vision”

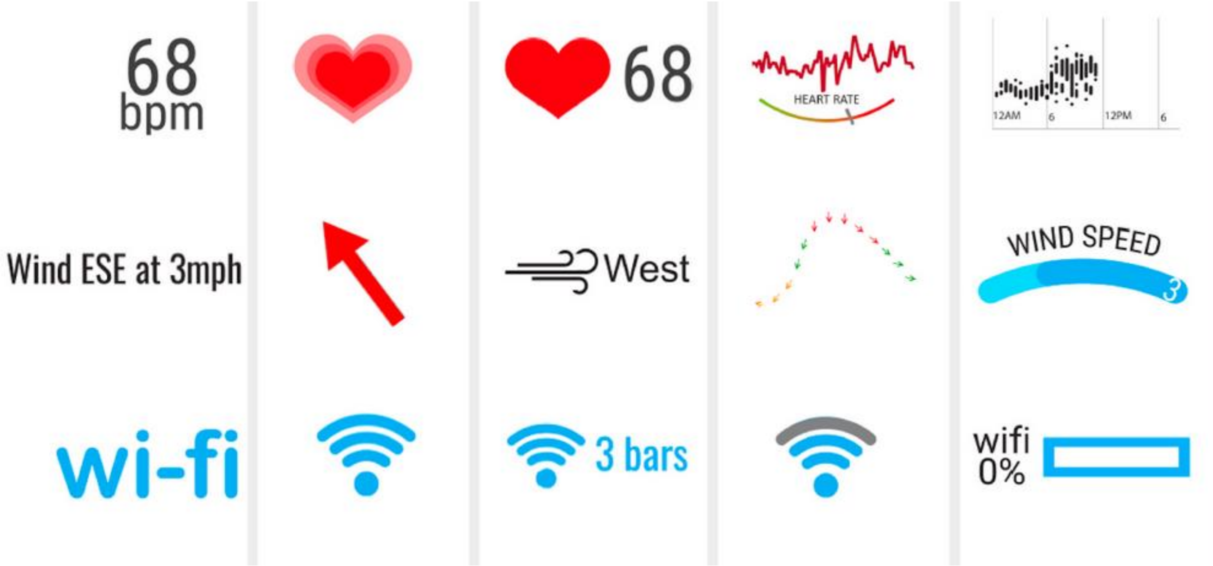


https://en.wikipedia.org/wiki/Eye_movement_in_reading

BUT…

…it is too early to discuss precise size ranges

The effect of reducing visualizations in size is still too poorly understood



Still limited evidence

On the effect of shrinking visualizations

On the Limits of Resolution and Visual Angle in Visualization

CHRISTOPHER G. HEALEY and AMIT P. SAWANT, North Carolina State University

This article describes a perceptual level-of-detail approach for visualizing data. Properties of a dataset that cannot be resolved in the current display environment need not be shown, for example, when too few pixels are used to render a data element, or when the element's subtended visual angle falls below the acuity limits of our visual system. To identify these situations, we asked: (1) What type of information can a human user perceive in a particular display environment? (2) Can we design visualizations that control what they represent relative to these limits? and (3) Is it possible to dynamically update a visualization as the display environment changes, to continue to effectively utilize our perceptual abilities? To answer these questions, we conducted controlled experiments that identified the pixel resolution and subtended visual angle needed to distinguish different values of luminance, hue, size, and orientation. This information is summarized in a perceptual display hierarchy, a formalization describing how many pixels—*resolution*—and how much physical area on a viewer's retina—*visual angle*—is required for an element's visual properties to be readily seen. We demonstrate our theoretical results by visualizing historical climatology data from the International Panel for Climate Change.

Categories and Subject Descriptors: H.1.2 [**Models and Principles**]: User/Machine Systems—*Human information processing*; I.3.3 [**Computer Graphics**]: Picture/Image Generation—*Viewing algorithms*; J.4 [**Computer Applications**]: Social and Behavioral Sciences—*Psychology*

General Terms: Experimentation, Human Factors

Additional Key Words and Phrases: Hue, orientation, luminance, resolution, size, visual acuity, visual angle, visual perception, visualization

ACM Reference Format:

Healey, C. G. and Sawant, A. P. 2012. On the limits of resolution and visual angle in visualization. ACM Trans. Appl. Percept. 9, 4, Article 20 (October 2012), 21 pages.
DOI = 10.1145/2355598.2355603 http://doi.acm.org/10.1145/2355598.2355603

20

1. INTRODUCTION

Scientific and information visualization convert large collections of strings and numbers into visual representations that allow viewers to discover patterns within their data. The focus of this article is the visualization of a *multidimensional* dataset containing m data elements and n data attributes, $n > 1$. As the *size* m and the *dimensionality* n of the dataset increase, so too does the challenge of finding techniques to display even some of the data in a way that is easy to comprehend [Johnson et al. 2006]. One promising approach to this problem is to apply rules of perception to generate visualizations that

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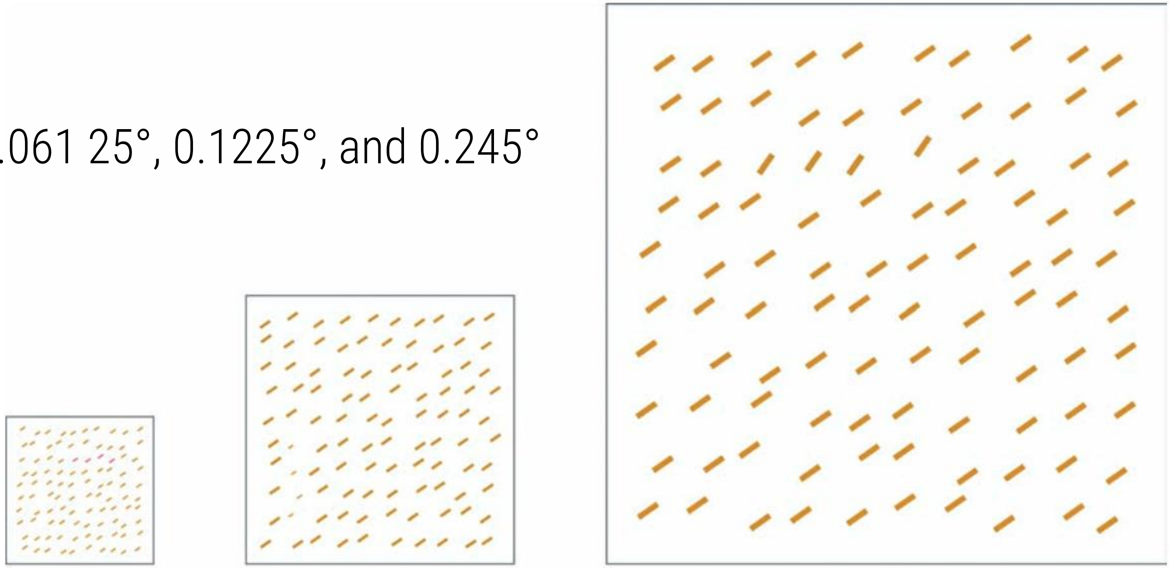
DOI 10.1145/2355598.2355603 http://doi.acm.org/10.1145/2355598.2355603

0.061 25°, 0.1225°, and 0.245°



(a) (b) (c)

Larger stimuli → faster responses

Visual Parameters Impacting Reaction Times on Smartwatches

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ABSTRACT

As a new generation of smartwatches enters the market, one common use is for displaying information such as notifications. While some content might warrant immediately interrupting a user, there is also information that might be important to display yet less urgent. It would be useful to show this content on the watch but not immediately draw the user's attention away from their primary task. In this paper, we investigate how fast three visual parameters draw a user's attention. In particular, we present data from a smartwatch user study where we examine the size, frequency, and color of a visual prompt and the associated impact on reaction time. We find statistically significant differences for size and frequency where smaller and slower result in the less immediate reactions. We also present reaction time distributions that a designer can use to tailor expected notification response times to match their content.

Keywords

Smartwatch; Notification; Reaction time; User study

Categories and Subject Descriptors

H.5.m. [**Information Interfaces and Presentation (e.g. HCI)**]: Miscellaneous

1. INTRODUCTION

Smartwatches are a form of wearable computing being adopted by the general public with many new products being developed. Many smartwatches provide a variety of functions by running different applications in conjunction with a user's mobile phone. One common use is to provide notifications of incoming communications or events. While notifications might be a useful capability, they must be treated with some caution. As Starner articulates: "user attention is the scarcest resource for wearable computing" [15]. If the user is to be interrupted, it should probably take as little time as possible [1]. However, even a very short interruption at an inopportune moment might be detrimental as it could divert a user's attention away from their primary real world task.

MobileHCI '16, September 06 - 09, 2016, Florence, Italy

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DOI: http://dx.doi.org/10.1145/2935334.2935344

Some approaches to this attention problem include using algorithms to filter and thus reduce the number of notifications or to model the user to infer when they might be more interruptible [5, 8, 14]. In this paper, we explore a complementary technique. We believe there are different kinds of content that can be shown on a smartwatch (or other wearable) that might have differing levels of urgency similar to ambient displays [10]. Some information needs to be attended to *immediately* such as an incoming phone call. For other content, it might be better if the user is not interrupted right away but sees the content in a timely way *eventually* (like for a social network update or a new weather forecast). To that end, we investigate how three different visual parameters on a smartwatch might have different demands on attention and associated user reaction times.

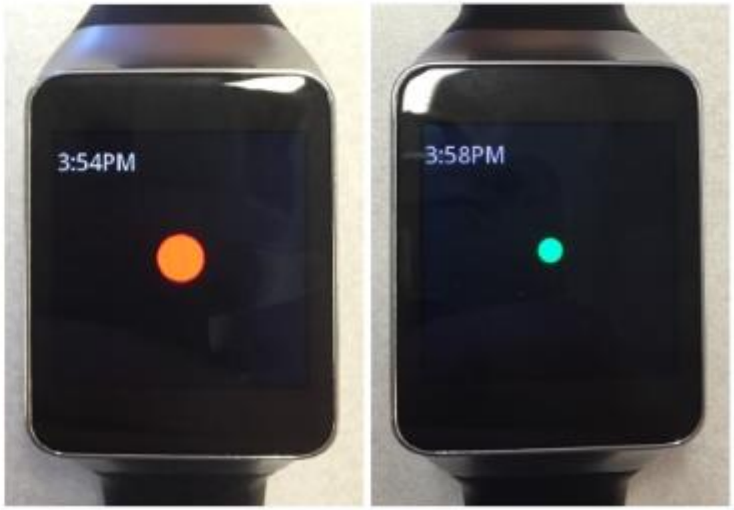
For example, if a designer or developer wants to very quickly alert the user and draw their attention to the smartwatch, which visual cues should they use? And just as importantly, if the designer does not want to immediately distract the user but wants them to notice information within a given time window (say within approximately two minutes), which stimulus should be used? Or from the opposite perspective, given a combination of visual parameters in a stimulus, how long should we expect it to take for a user to notice and respond?

This goal leads to our research question: how does manipulating the parameters of a visual stimulus on a smartwatch impact visual attention and therefore user reaction time? We examine three different parameters of visual stimuli that can be shown on a smartwatch to understand how manipulating those parameters alters how long it takes a user to notice and respond. In particular, we manipulate the size, color and frequency of a visual stimulus in a user study where participants wore a smartwatch as part of their otherwise daily routine. We measure the time from when a stimulus is presented to when a participant notices and dismisses it with a touch on the smartwatch (the reaction time). If we are able to alter this time, we are further interested in understanding the resulting time distributions. These distributions can then inform the design process to intentionally shorten or lengthen the expected reaction time to match the urgency needs of different types of content shown on the smartwatch.

2. RELATED WORK

Smartwatches have a long history in the research domain. For example, the IBM Linux watch [12, 13] investigated the challenges of miniaturizing a general purpose computer into a watch form factor. The eWatch began exploring aspects we are now seeing in some smartwatches such as the role of sensors on watches for activity recognition and using the watch for notifications [11].

Wearable notifications have been explored in a variety of user studies. For example, Ashbrook *et al.* evaluated the time to react to



(a) (b)

Figure 1: Example stimuli from our study shown on the Samsung Gear Live. a) is the red 5.0mm condition while b) is the green 2.5mm condition.

participants reacted faster to notifications shown as larger circles

Sizing the Horizon: The Effects of Chart Size and Layering on the Graphical Perception of Time Series Visualizations

Jeffrey Heer[1], Nicholas Kong[2], and Maneesh Agrawala[2]

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ABSTRACT
We investigate techniques for visualizing time series data and evaluate their effect in value comparison tasks. We compare line charts with *horizon graphs*—a space-efficient time series visualization technique—across a range of chart sizes, measuring the speed and accuracy of subjects' estimates of value differences between charts. We identify transition points at which reducing the chart height results in significantly differing drops in estimation accuracy across the compared chart types, and we find optimal positions in the speed-accuracy tradeoff curve at which viewers performed quickly without attendant drops in accuracy. Based on these results, we propose approaches for increasing data density that optimize graphical perception.

Author Keywords
Visualization, graphical perception, time series, line charts, horizon graphs.

ACM Classification Keywords
H.5.2. Information Interfaces: User Interfaces.

INTRODUCTION
Time series—sets of values changing over time—are one of the most common forms of recorded data. Time-varying phenomena are central to many areas of human endeavor and analysts often need to simultaneously compare a large number of time series. Examples occur in finance (e.g., stock prices, exchange rates), science (e.g., temperatures, pollution levels, electric potentials), and public policy (e.g., crime rates), to name just a few. Accordingly, visualizations that improve the speed and accuracy with which human analysts can compare and contrast time-varying data are of great practical benefit.

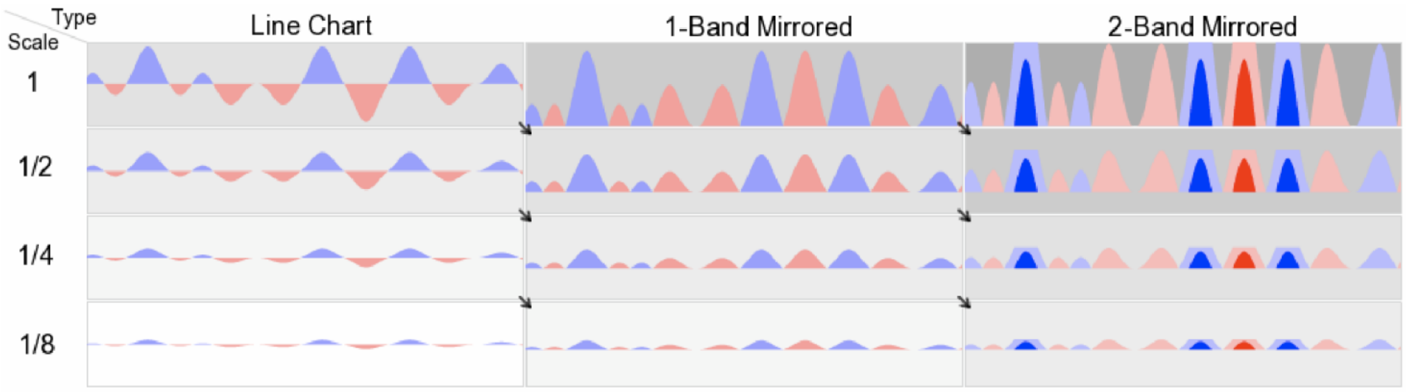
Effective presentation of multiple time series is an instance of a larger problem in visualization research: increasing the

Figure 1. (a) Filled line chart. Area between data values on line and zero is filled in. **(b) "Mirrored" chart.** Negative values are flipped and colored red, cutting the chart height by half. **(c) 2-band horizon graph.** The chart is divided into bands and overlaid, again halving the height.

amount of data with which human analysts can effectively work. Toward this aim, researchers and designers have devised design guidelines and visualization techniques for making more effective use of display space. Tufte [27] advises designers to maximize data density (data marks per chart area) and researchers regularly promote visualization techniques (e.g., [12, 22, 25]) for their "space-filling" properties. Such approaches excel at increasing the amount of information that can be encoded within a display. However, increased data density does not necessarily imply improved graphical perception for visualization viewers.

Consider the three time series charts in Figure 1. The first graph is a filled line chart—a line chart with the area between the data value on the line and zero filled in. The second graph "mirrors" negative values into the same region as positive values, and it relies on hue to differentiate between the two. The mirror chart doubles the data density compared to the line chart. The third chart, called a *horizon graph* [7], further reduces space use by dividing the chart into bands and layering the bands to create a nested form. With two layered bands the horizon graph doubles the data density yet again.

Such increases in data density enable designers to display more charts in a fixed area and thereby make it easier for viewers to compare data across multiple charts. Yet, mirroring negative values, dividing the series into bands, and layering the bands may also obscure patterns in the data



small chart heights negatively affected accuracy and speed of data comparison

smaller size had a greater impact on the filled line charts than on the Horizon Graphs

Volume xx (200y), Number z, pp. 1–12

A Study of the Effect of Donut Chart Parameters on Proportion Estimation Accuracy

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[2]University of Groningen, Johann Bernoulli Institute for Mathematics and Computer Science, The Netherlands
[3]Hangzhou Dianzi University, China

Abstract

Pie and donut charts nicely convey the part-whole relationship and they have become the most recognizable chart types for representing proportions in business and data statistics. Many experiments have been carried out to study human perception of the pie chart, while the corresponding aspects of the donut chart have seldom been tested, even though the donut chart and the pie chart share several similarities. In this paper we report on a series of experiments in which we explored the effect of a few fundamental design parameters of donut charts, and additional visual cues, on the accuracy of such charts for proportion estimates. Since mobile devices are becoming the primary devices for casual reading we performed all our experiments on such device. Moreover, the screen size of mobile devices is limited and it is therefore important to know how such size constraint affects the proportion accuracy. For this reason, in our first experiment we tested the chart size and we found that it has no significant effect on proportion accuracy. In our second experiment, we focused on the effect of the donut chart inner radius and we found that the proportion accuracy is insensitive to the inner radius, except the case of the thinnest donut chart. In the third experiment we studied the effect of visual cues and found that marking the center of the donut chart or adding tickmarks at 25% intervals improves the proportion accuracy. Based on the results of the three experiments we discuss the design of donut charts and offer suggestions for improving the accuracy of proportion estimates.

1. Introduction

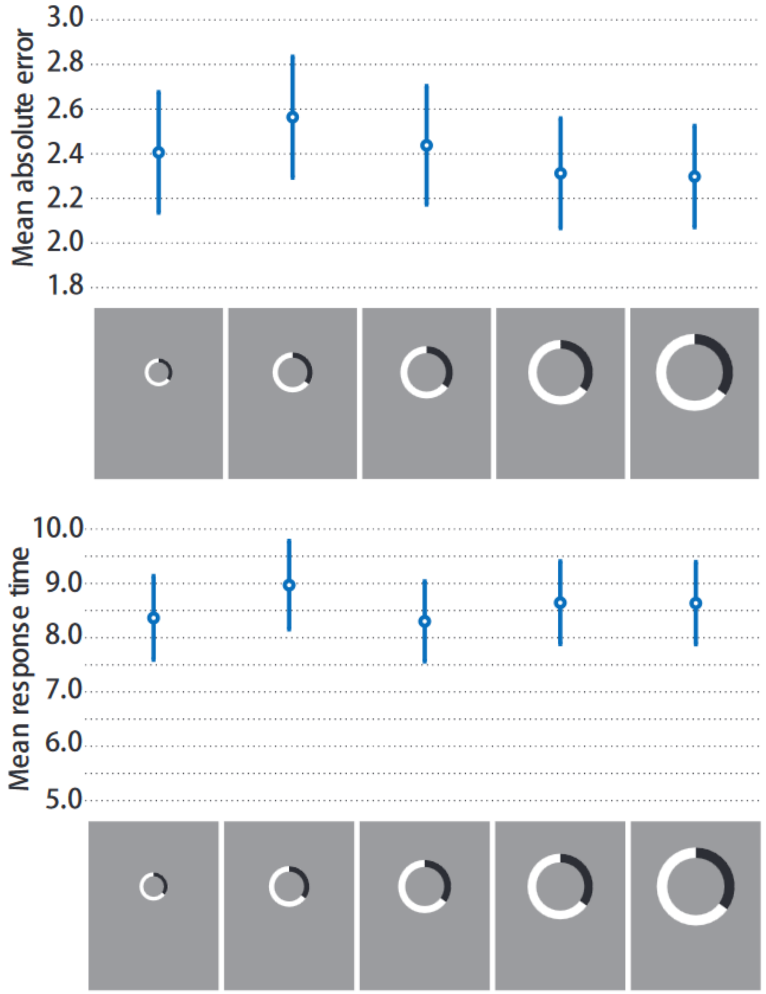
The donut chart is a variant of the pie chart, where a center disk has been removed and the remaining ring is divided into slices, see Fig. 1. Both types of charts, donut and pie, nicely convey the part-whole relationship, and for this reason they are being extensively used for showing proportions. Despite its prevalence, the pie chart has long been criticized by information visualization experts. The history of the pie chart and the debate around its use has been reviewed in, among others, [Spe05] and [SL91].

Donut charts share several similarities with pie charts and one can consider the latter as a special case of the former where the inner radius becomes zero. Compared to pie charts, donut charts have the advantage that their structure can be adapted to the presentation of extra information. Some common adaptations are multi-level donut charts and "sunbursts" [SZ00] supporting the representation of hierarchical data by using multiple rings, and chord diagrams [KSB*09] where the hole is used for drawing connections between different slices. At the same time, donut charts emphasize different visual encodings compared to pie charts. For example, in pie charts, explicit information of angle can be leveraged to estimate proportions while in donut charts angle can be only indirectly inferred. Such differences mean that study results for pie charts cannot be directly applied to donut charts.

Many experiments (e.g. [SH87, SL91]) have been carried out on human perception of the pie chart, mainly focusing on its accuracy and effectiveness. Studies comparing pie charts to "rectangular" charts (such as bar charts or waffle charts) show that the former are not inferior to the latter for proportion estimation as we describe in detail in the review of related work in Sec. 2. However, "round" charts are perceived differently than "rectangular" charts [ZK10a, ZK10b] and hence their use may be preferable in certain contexts. Moreover, as described in the previous paragraph, donut charts have advantages that make them suitable for specific graphical representations.

The aim of the present work is not to compare donut charts to other chart types but to find out how to improve the proportion estimation accuracy of donut charts for those cases where the use of such charts is preferred. We study this question in two, complementary, ways. First, we determine how the two fundamental design parameters of donut charts (outer and inner radius) affect the accuracy of proportion estimates. Second, we explore the effect of additional visual cues on the accuracy so that we can make specific suggestions on the use of such cues in the design of donut charts. We

submitted to COMPUTER GRAPHICS *Forum* (12/2017).



~ 3.3°–9°

no clear evidence of a difference

The Complexity of Micro Visualizations

As a display space challenge

COMPLEXITY

- External
- Interaction
- Mediated
- ~~Internal (not here)~~

Complex Interaction

LARS-ERIK JANLERT
Umeå University
and
ERIK STOLTERMAN
Indiana University

An almost explosive growth of complexity puts pressure on people in their everyday doings. Digital artifacts and systems are at the core of this development. How should we handle complexity aspects when designing new interactive devices and systems? In this article we begin an analysis of *interaction complexity*. We portray different views of complexity; we explore not only negative aspects of complexity, but also positive, making a case for the existence of *benign* complexity. We argue that complex interaction is not necessarily bad, but designers need a deeper understanding of interaction complexity and need to treat it in a more intentional and thoughtful way. We examine interaction complexity as it relates to different loci of complexity: *internal*, *external*, and *mediated* complexity. Our purpose with these analytical exercises is to pave the way for design that is informed by a more focused and precise understanding of interaction complexity.

Categories and Subject Descriptors: D.2.2 [**Software Engineering**]: Design Tools and Techniques—*User interfaces*; H.5.2 [**Information Interfaces and Presentation**]: User Interfaces—*Graphical user interfaces (GUIs)*

General Terms: Design

Additional Key Words and Phrases: Interaction complexity, interface design, design approach, design theory, product design, benign complexity

ACM Reference Format:

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DOI = 10.1145/1746259.1746262 http://doi.acm.org/10.1145/1746259.1746262

1. INTRODUCTION

Modern information technology tends to increase the complexity of artifacts, whether they are small, personal devices or huge systems like industrial plants

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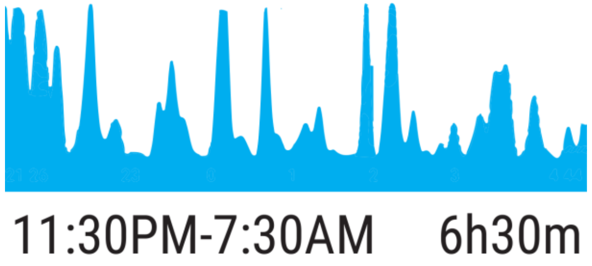
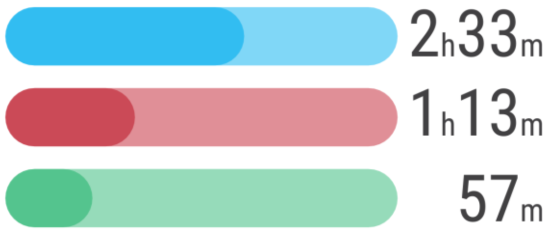
DOI 10.1145/1746259.1746262 http://doi.acm.org/10.1145/1746259.1746262

ACM Transactions on Computer-Human Interaction, Vol. 17, No. 2, Article 8, Publication date: May 2010.

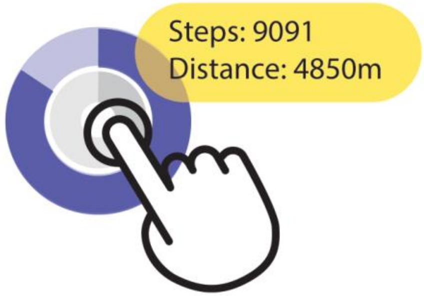
EXTERNAL Complexity
(apparent & real)



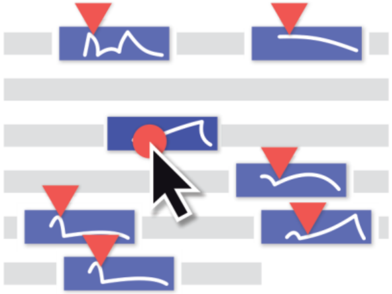


INTERACTION Complexity

Simple view change interaction



Tap for details-on-demand

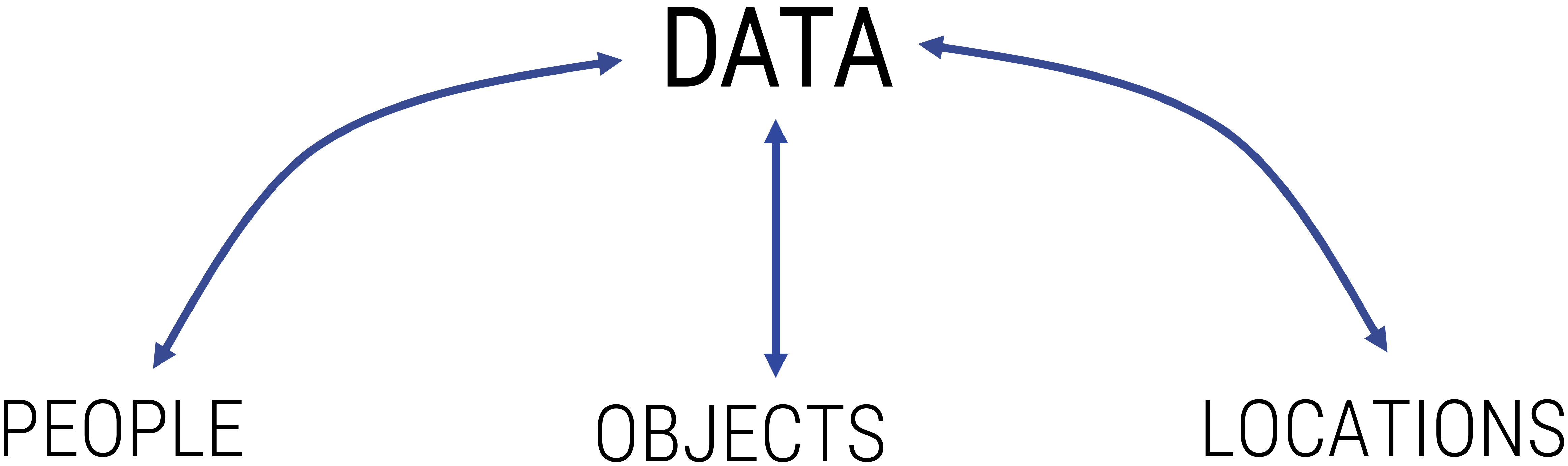


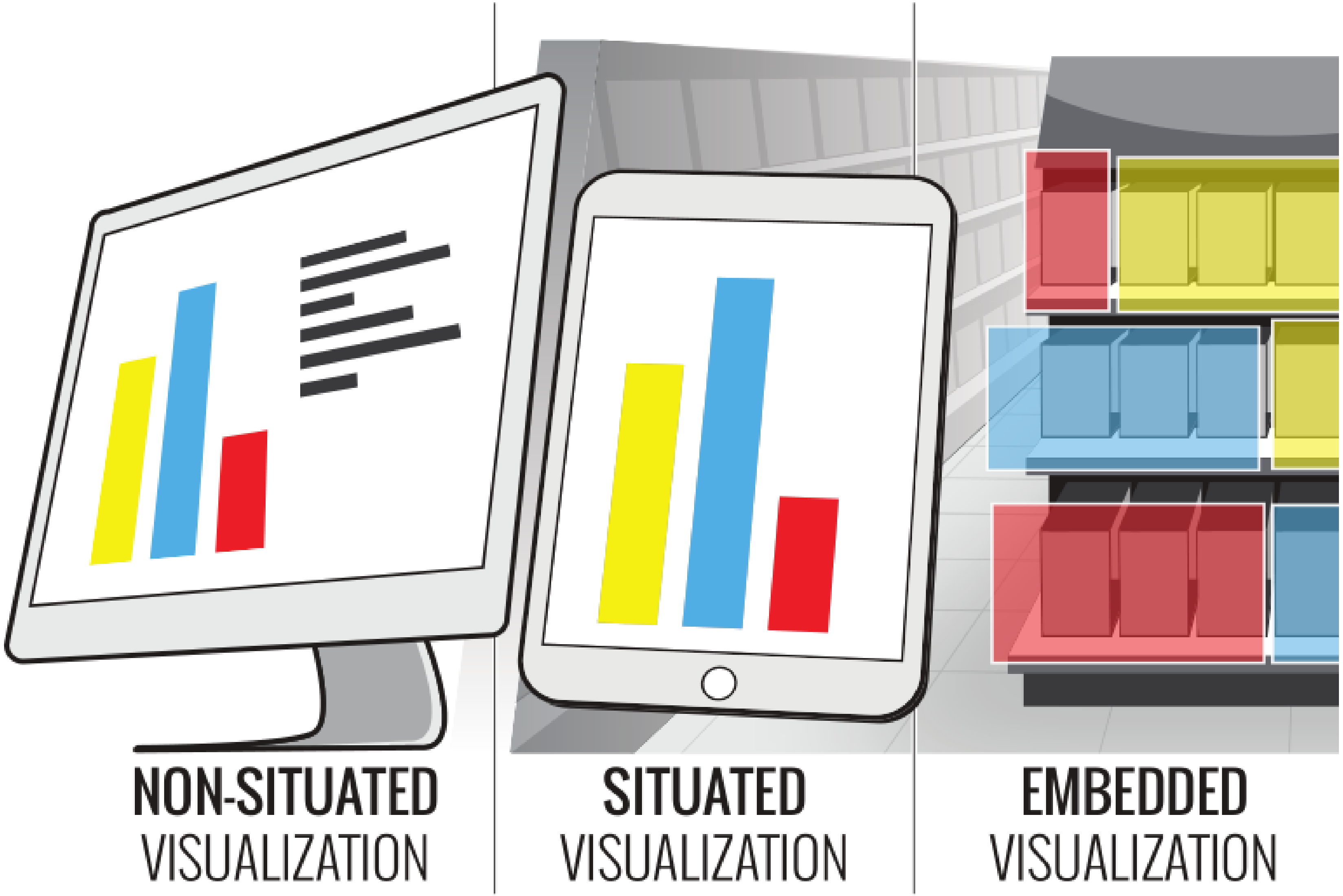
Brushing and linking as part of a complex interactive micro visualization setup.

MEDIATED Complexity

SITUATEDNESS

Situated and Embedded Data Representation


DATA
PEOPLE
OBJECTS
LOCATIONS


NON-SITUATED
VISUALIZATION
SITUATED
VISUALIZATION
EMBEDDED
VISUALIZATION

Visualization about oneself or one’s surrounding on wearable device

= situated / embedded visualization

Mobile Visualization Design: An Ideation Method to Try

Sheelagh Carpendale, Simon Fraser University

Petra Isenberg, Université Paris-Saclay, CNRS, Inria, LISN

Charles Perin, University of Victoria

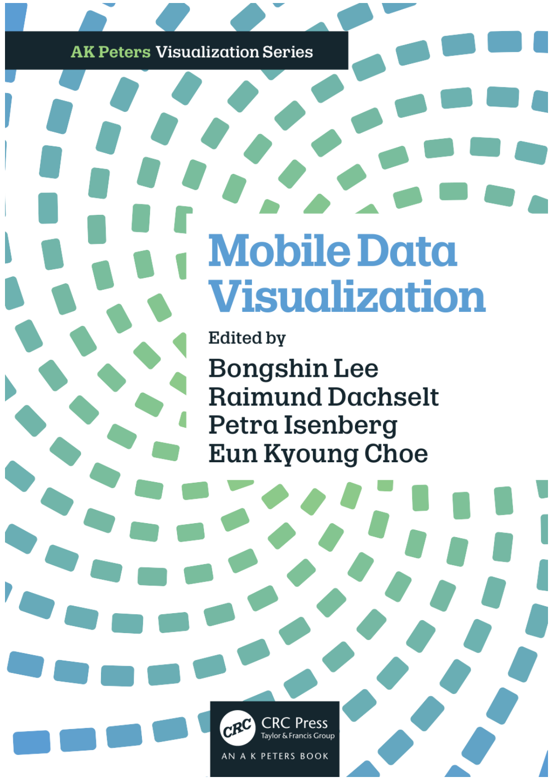
Tanja Blascheck, University of Stuttgart

Foroozan Daneshzand, Simon Fraser University

Alaul Islam, Université Paris-Saclay, CNRS, Inria, LISN

Katherine Currier, University of Calgary

Peter Buk, Victor Cheung, Lien Quach, Laton Vermette, Simon Fraser University



Research Methodology

- Explored the city of Stuttgart, Germany in a large team
- Stopped at each sight after 30 minutes
- Evaluated our information needs in the current situation
- Sketched a visualization on a prop
- Pairs of team members discussed their ideas and added comments, adjustments or variations to their notes and sketches

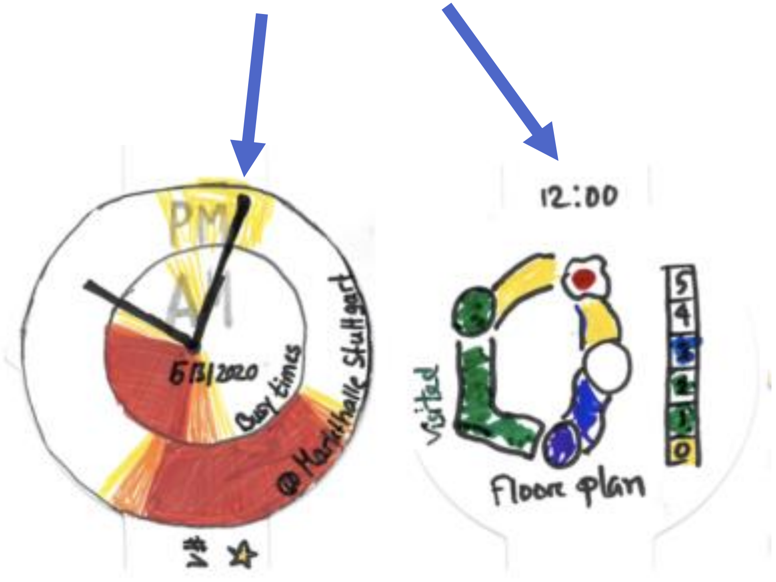
Slide adapted from Alaul Islam

47

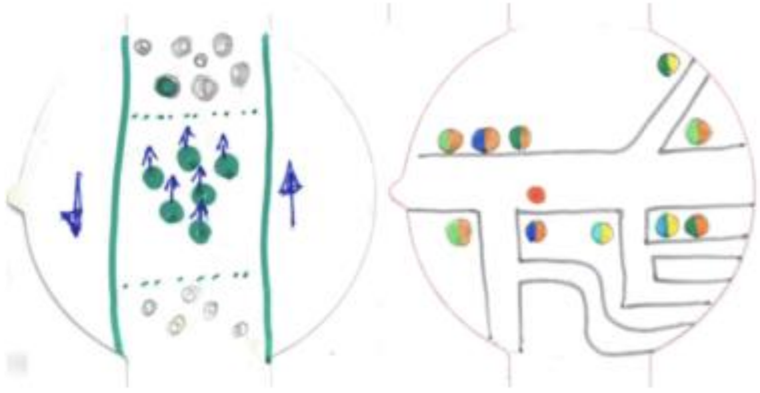
Visualization designs for smartwatches

Slide adapted from Alaul Islam

Data and Watch Functions



52%
Watchfaces



48%
Apps

https://osf.io/vhn43/

Information Needs

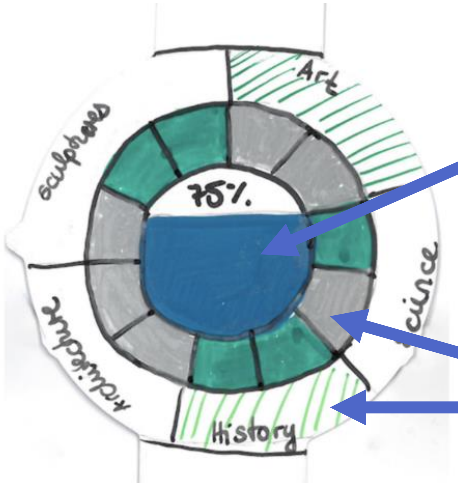
Additional context-specific information

Tracking information from activities

Reminders, todos

Data Representations

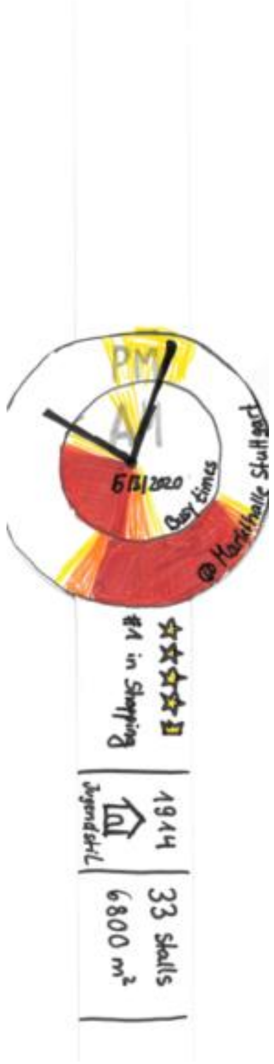
Many bespoke visualizations using known techniques



Bar chart

Stripe chart/1D matrix

Map with icons



Visualizations beyond the display

What did we learn about smartwatch visualizations?

- We can do better than transfer from large to small
- Visualizations adapted to entire device
- Time is a critical feature
- Information needs based on context

Visualizing Information on Watch Faces: A Survey with Smartwatch Users

Alaul Islam*
Université Paris-Saclay, CNRS, Inria, LRI

Anastasia Bezerianos†
Université Paris-Saclay, CNRS, Inria, LRI

Bongshin Lee‡
Microsoft Research

Tanja Blascheck§
University of Stuttgart

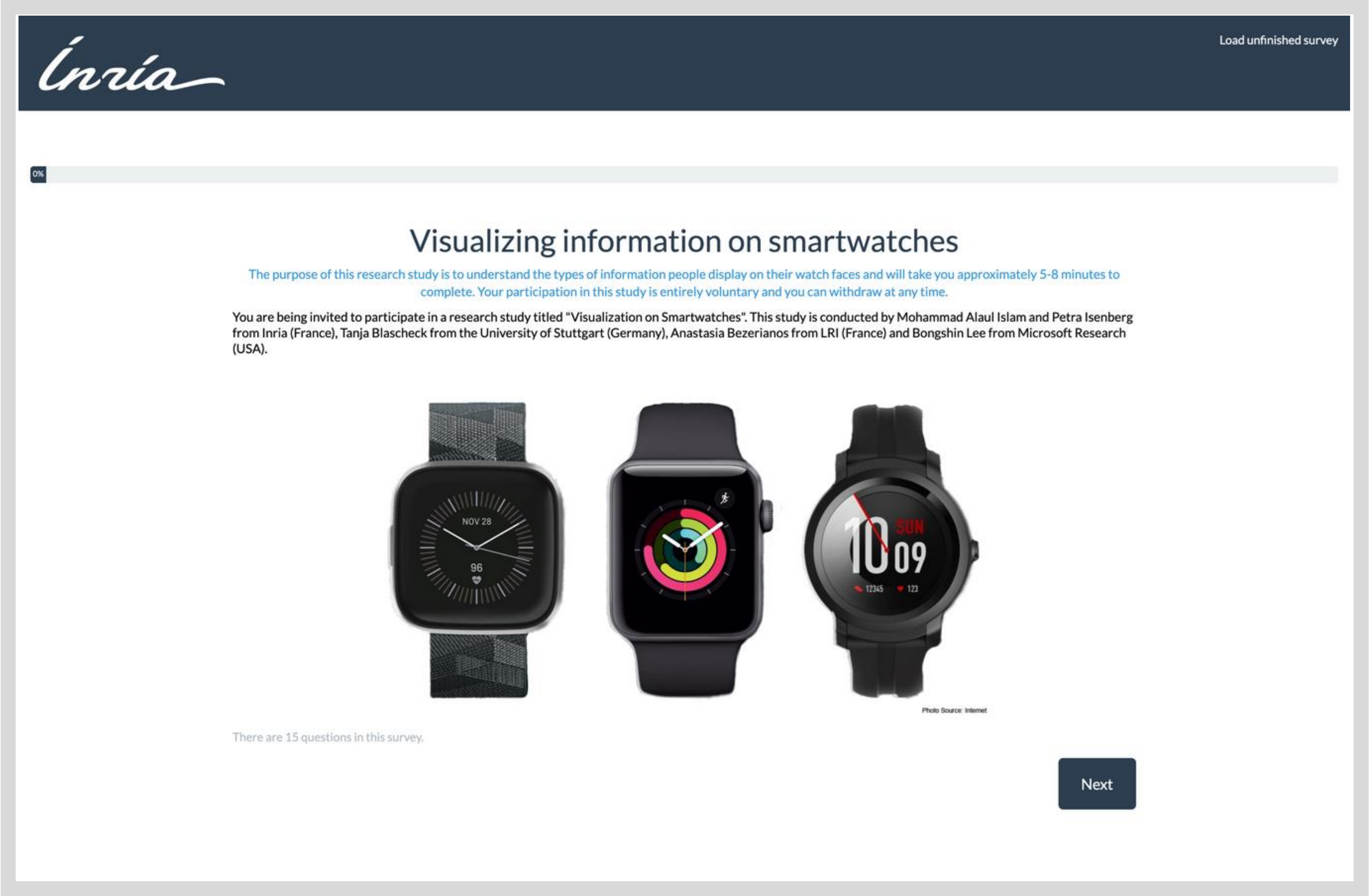
Petra Isenberg*
Université Paris-Saclay, CNRS, Inria, LRI

Figure 1: Smartwatch face examples (from Facer [13]) with increasing amounts of data items and representation types. From left to right: Material Volcano (BlueIceshard), Pie Charts II (Sunny Liao), Minimal Colors H (AK Watch), and Earthshade (Brad C). The graph on the right shows common pairs of data types displayed on the watch faces our 237 survey participants used. Circle colors correspond to three data categories: Health & Fitness, Weather & Planetary, and Device & Location.

Islam et al, IEEE Visualization (VIS), 2020 Short Paper

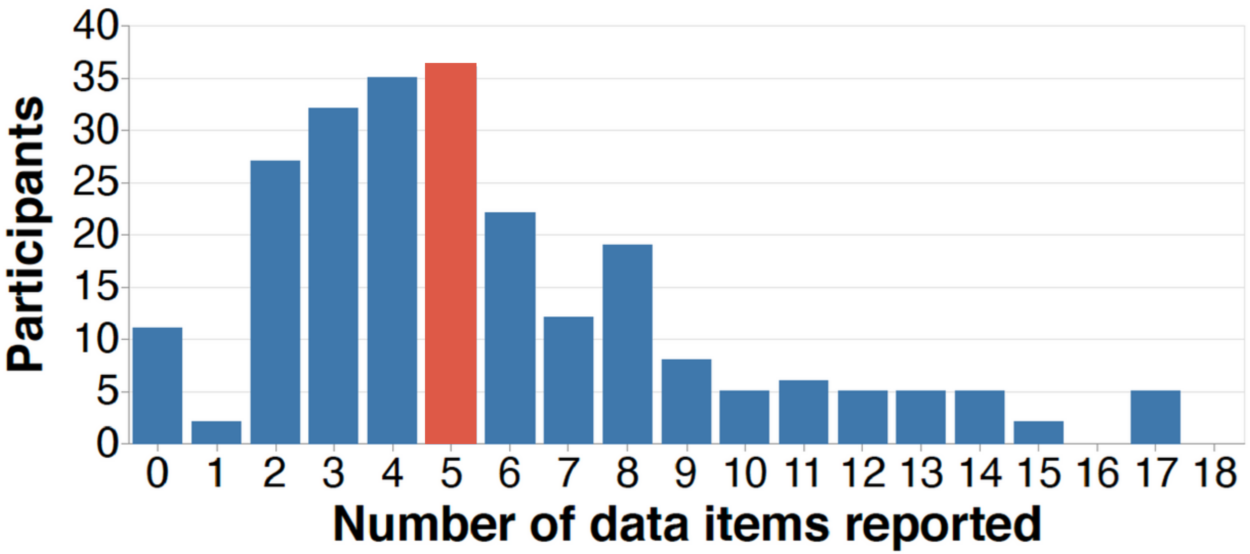
Methodology

Survey with smartwatch wearers about their current watch face

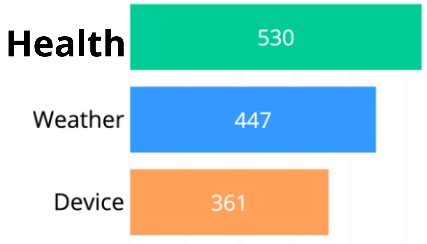


General Findings

- 237 valid responses
- On average 5 different data items displayed on watch face



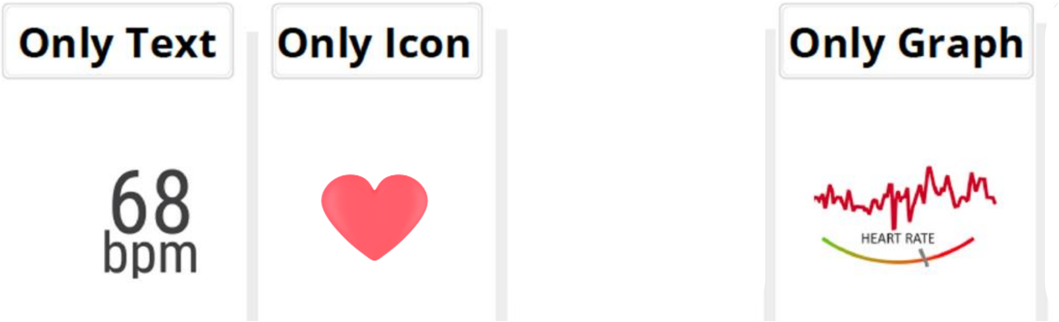
Which data types do people show on their watch faces?



Slide from Alaul Islam

Data with different representation types

very rare ☹



REPRESENTATIONS

What did we learn about smartwatch visualizations?

- Charts are rare
  - why?
- Icons are very common
  - Can we use them for visualization?
- Smartwatches show lots of data in small space
  - Can we read multiple items?
  - How quickly can we read them?
  - How should they be arranged?

QUICK GLANCES

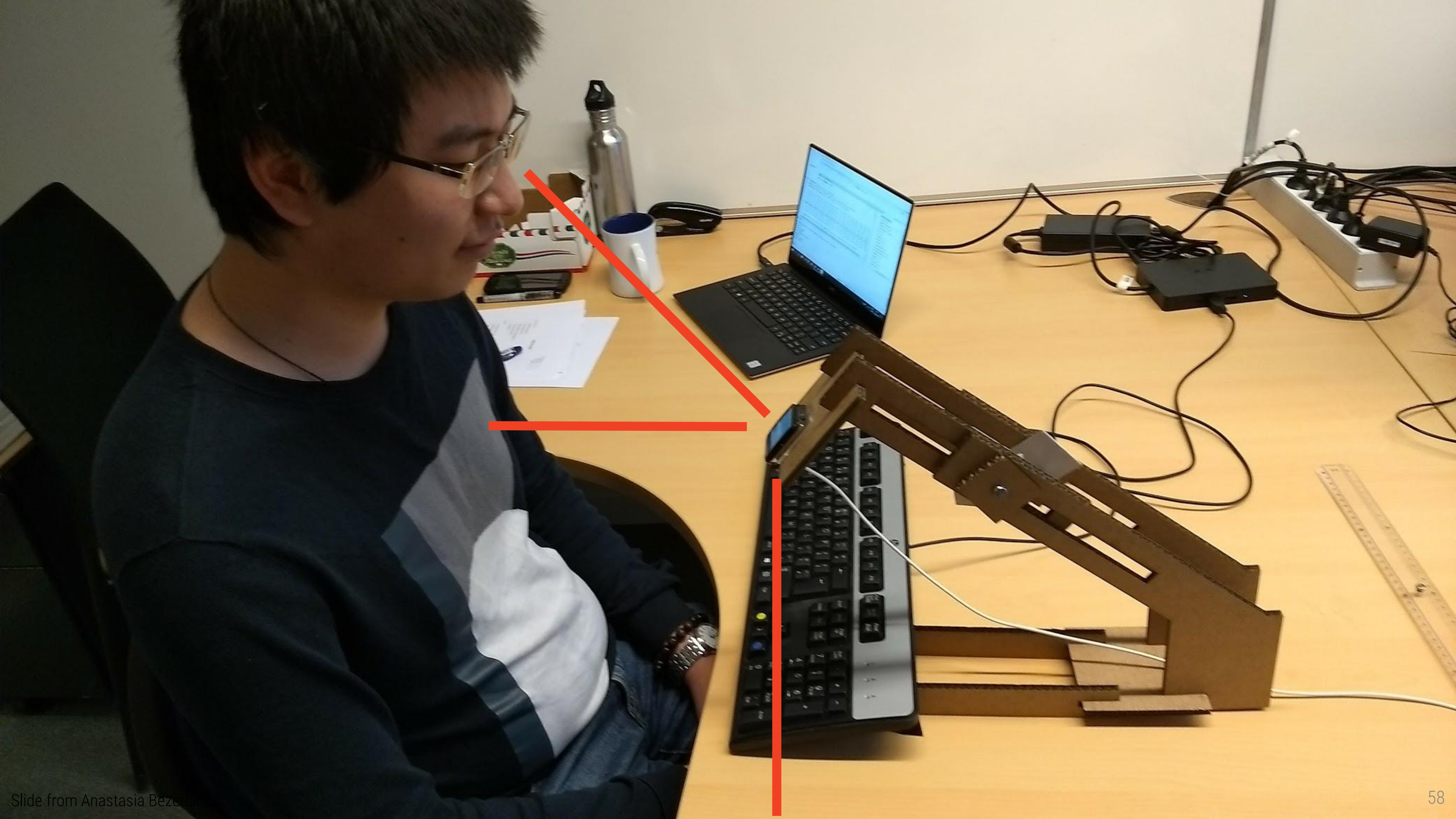
Perception

Research Questions

How fast can visualizations be read?

How accurately can small visualizations be read?

Slide from Anastasia Bezerianos



Slide from Anastasia Bezerianos

Preparing for Perceptual Studies:

Position and Orientation of Wrist-worn Smartwatches for Reading Tasks

Tanja Blascheck
Anastasia Bezerianos
Lonni Besançon
Bongshin Lee
Petra Isenberg

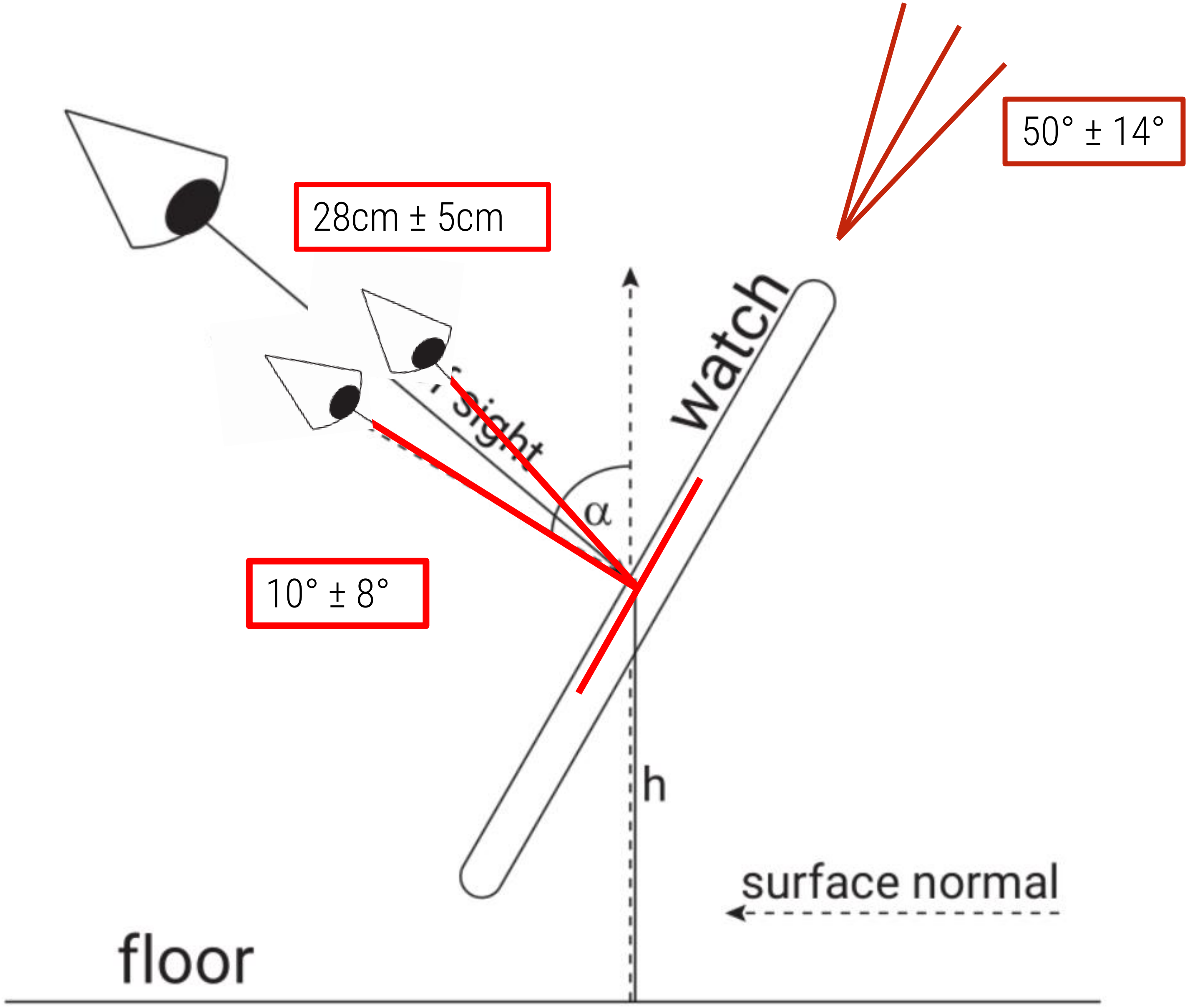
Workshop on Data Visualization on Mobile Devices held at ACM CHI, 2018

How to find the right setup?

Ran our own study

for seated participants
for standing participants

Model

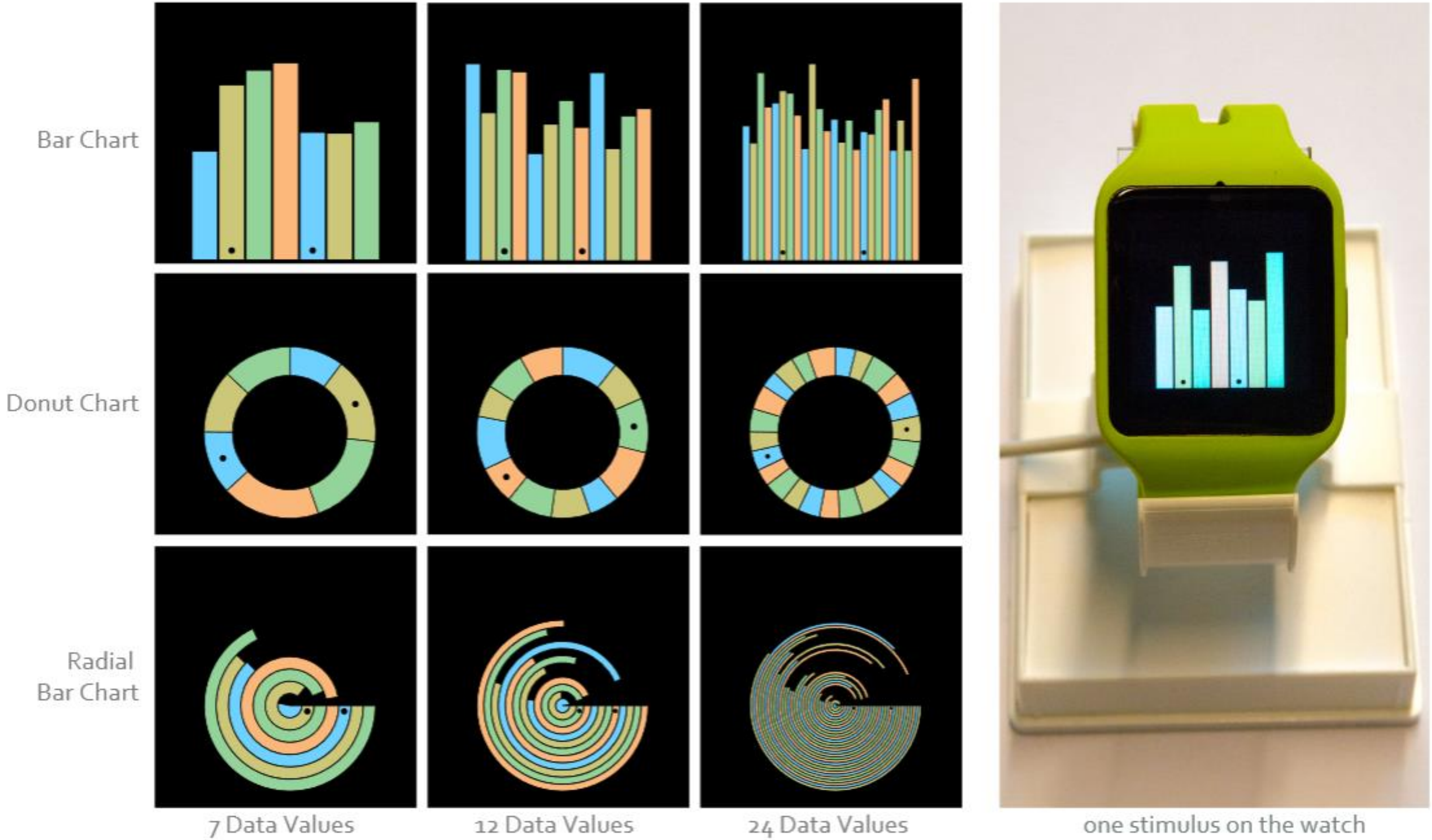


Glanceable Visualization: Studies of Data Comparison Performance on Smartwatches

Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, and **Petra Isenberg**

InfoVis 2018

Microsoft Research Inria INVENTEURS DU MONDE NUMÉRIQUE


Bar Chart
Donut Chart
Radial
Bar Chart
7 Data Values
12 Data Values
24 Data Values
one stimulus on the watch

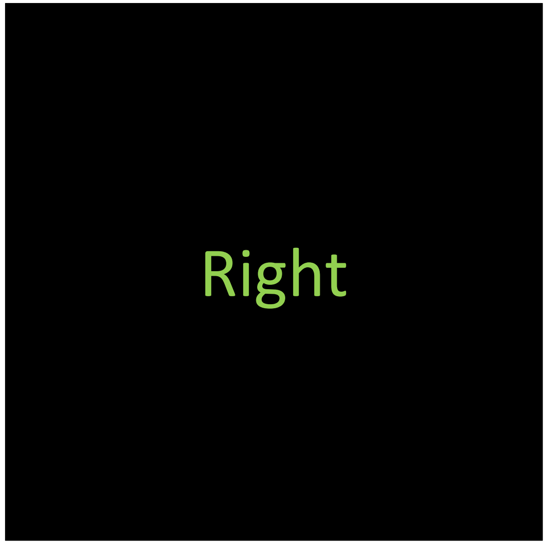
TASK

Data comparison
“Which bar is higher” ?

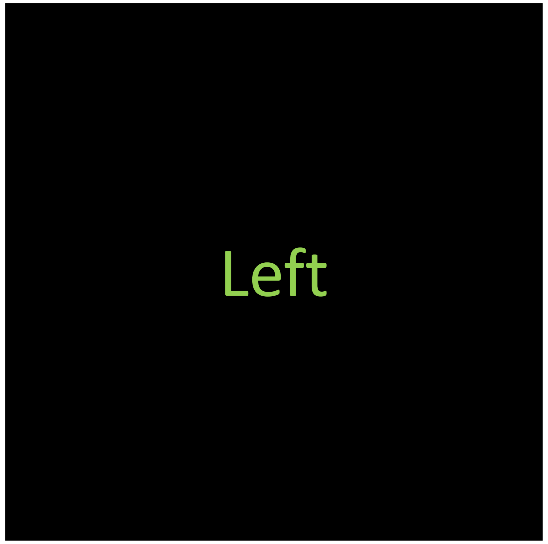
Which target is larger?

Left

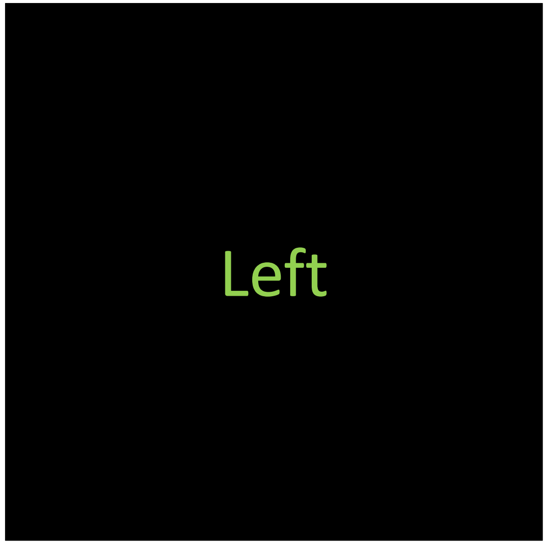
Which target is larger?



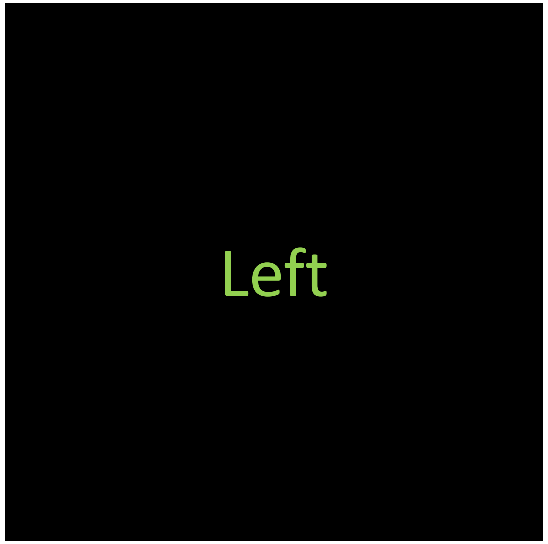
Which target is larger?



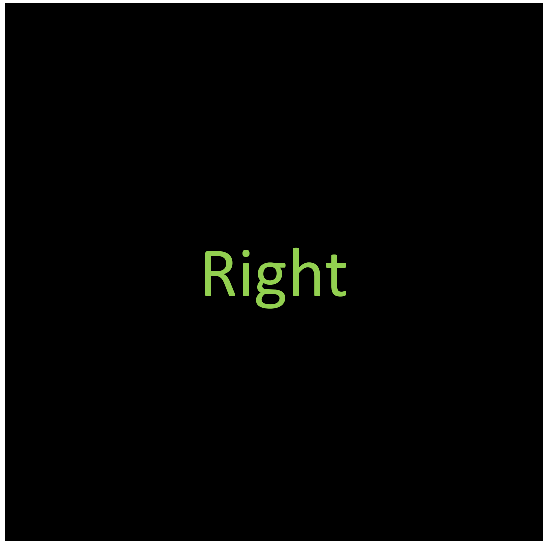
Which target is larger?



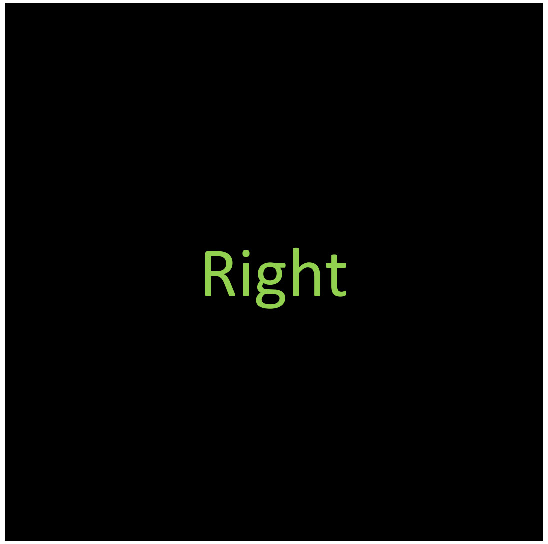
Which target is larger?



Which target is larger?



Which target is larger?



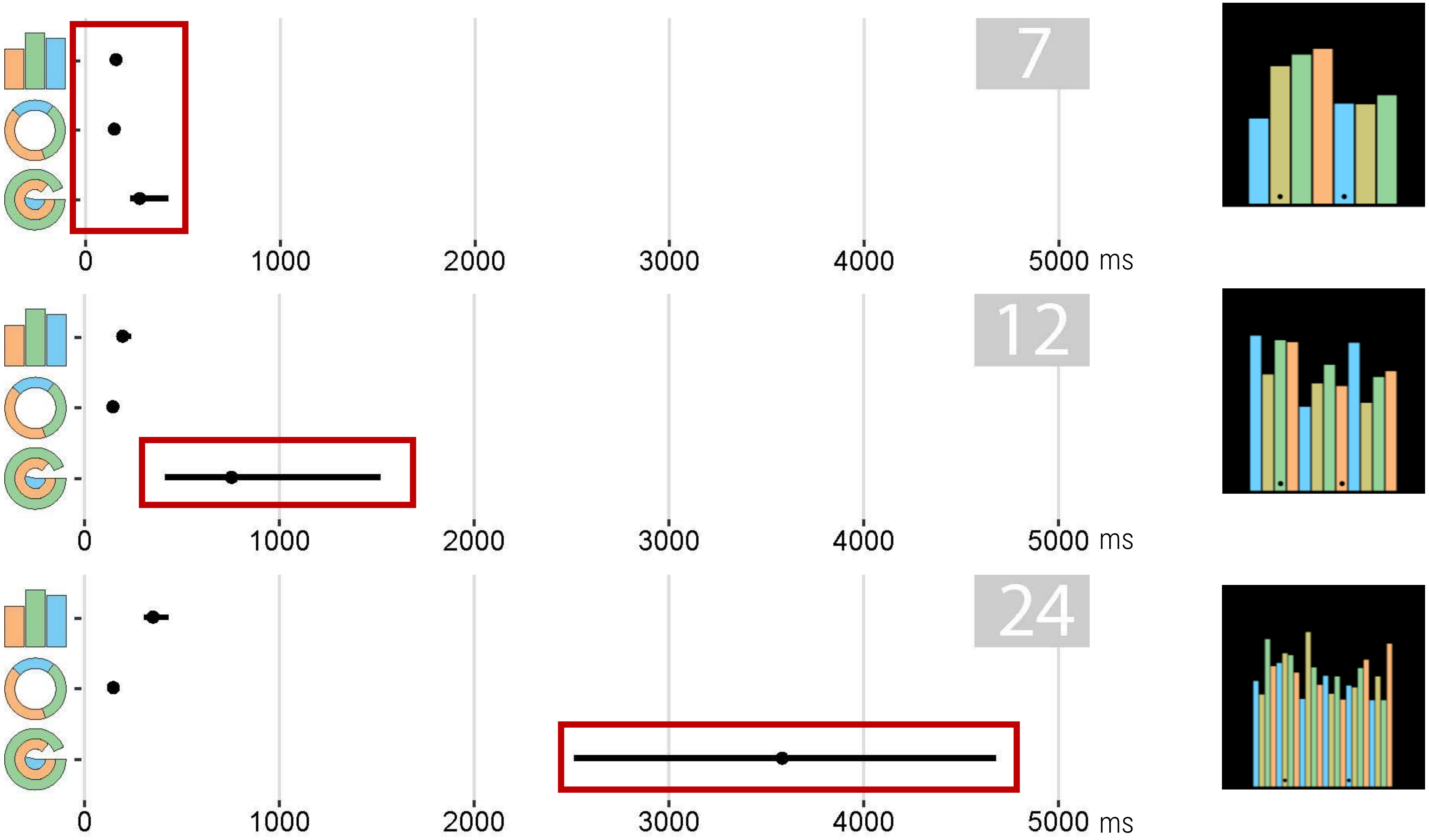
Which target is larger?

Right

Which target is larger?

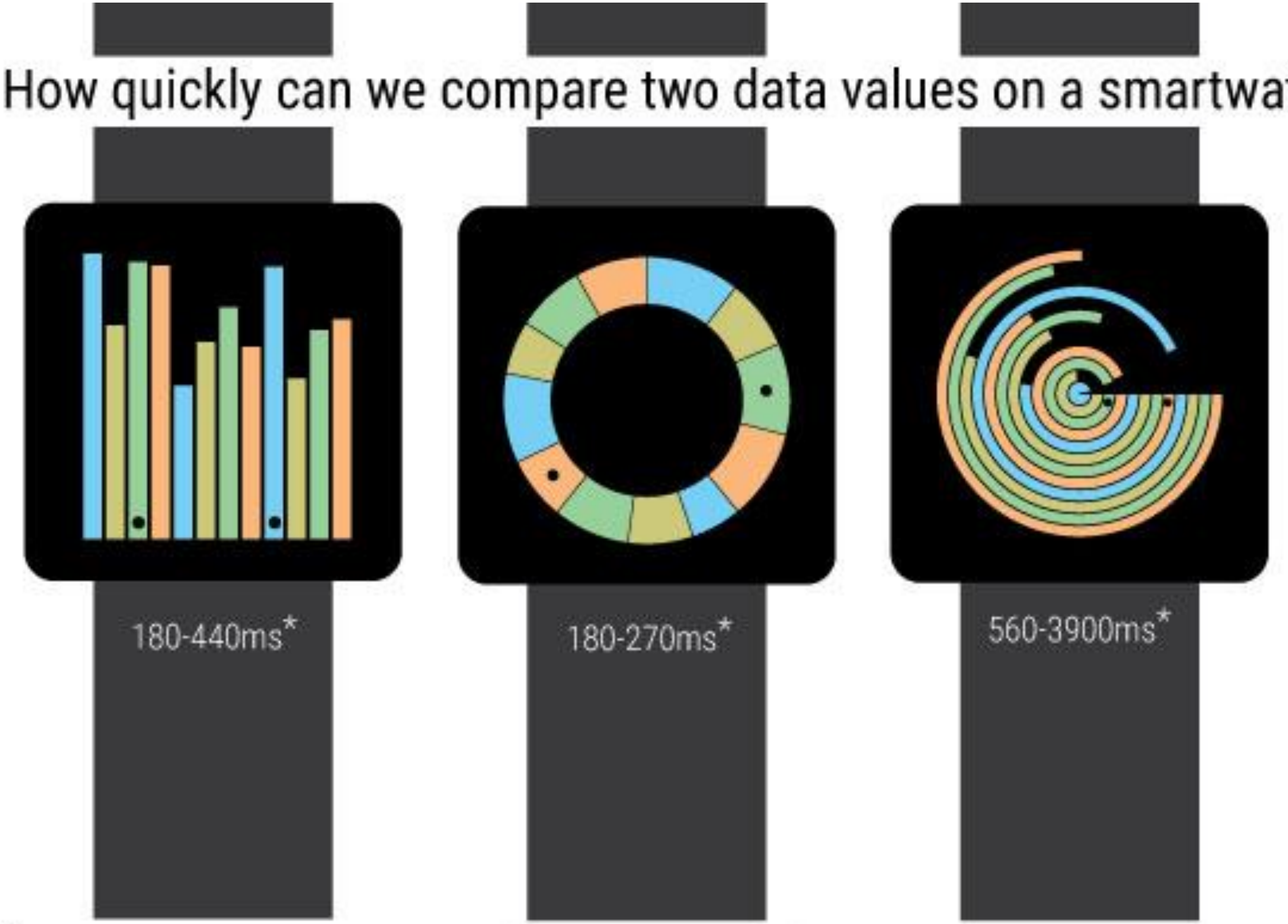
Left

Results



error bars are 95% CIs

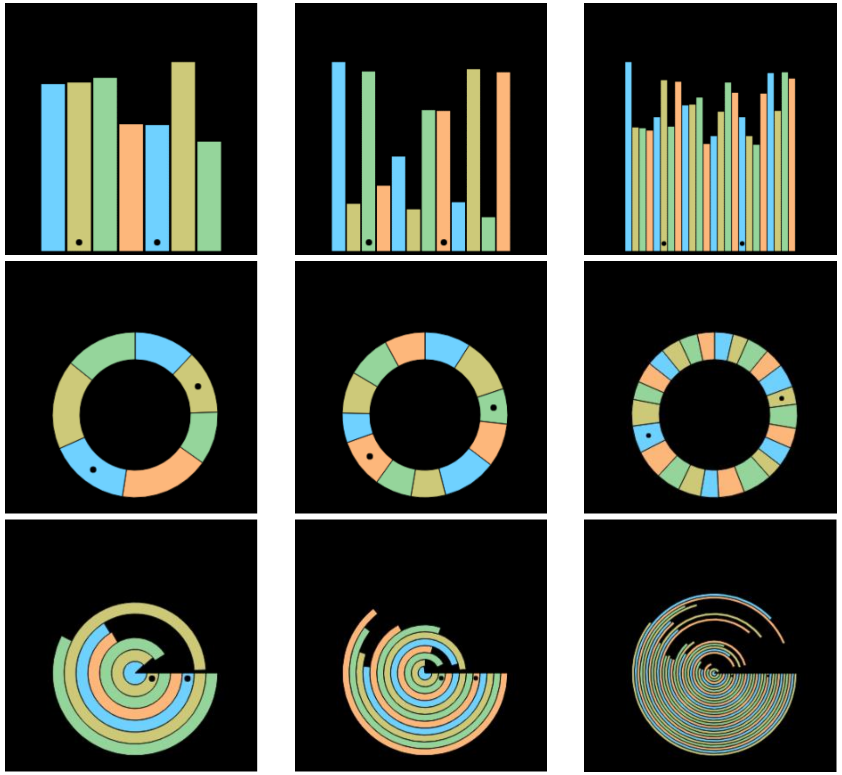
How quickly can we compare two data values on a smartwatch?



*depending on number of data items (we tested 7, 12, & 24)

What did we learn about smartwatch visualizations?

- People can perform comparison task VERY quickly with bar and donut charts
  - What about other tasks?
  - What about smaller visualizations?
- …even relatively “complex” visualizations
  - Are there thresholds?
  - What about more complex contexts?



Studies of Part-to-Whole Glanceable Visualizations on Smartwatch Faces

Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, Alaul Islam, Tingying He, Petra Isenberg

PacificVis 2023

université PARIS-SACLAY Microsoft Research Inria INVENTEURS DU MONDE NUMÉRIQUE

Reading Multiple Representations at Once

Can this be done at a glance?

How does the representation type matter?

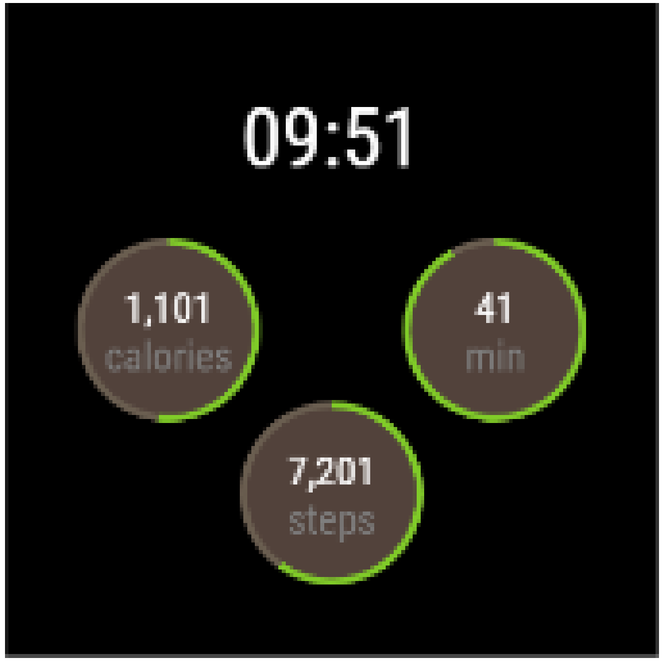
How does the complexity of the watch face matter?

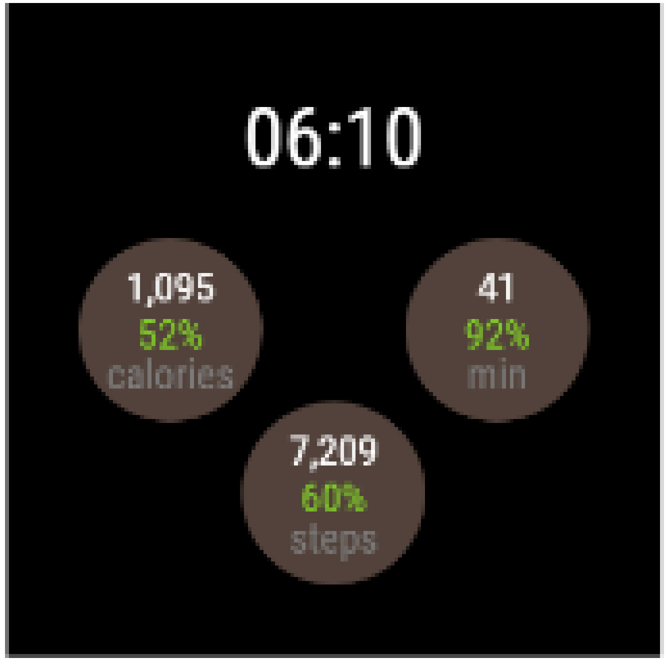
How does the viewing angle matter?

Task

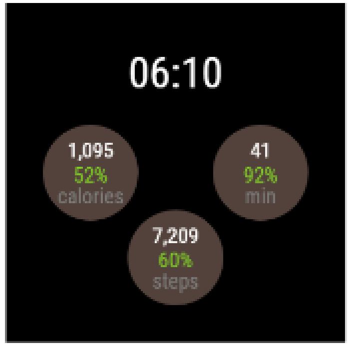
In how many fitness categories have you reached >66% of your goal?


16:48
1,092
calories
41
min
7,207
steps


09:51
1,101
calories
41
min
7,201
steps

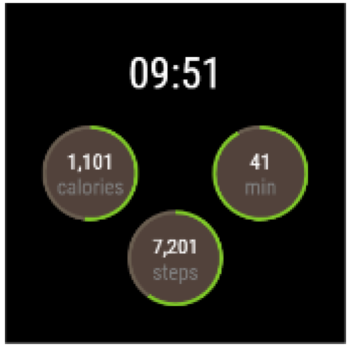

06:10
1,095
52%
calories
41
92%
min
7,209
60%
steps

Results



503ms , 31% error

↓ slower & more errors than



397ms , 26% error

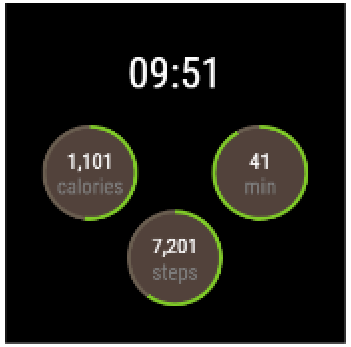
slower & more errors than

↓ slower & more errors than (but difference is very small)

318ms, 24% error

Results

Most visually pleasing



Exp 2: Does an analog watch face distract?

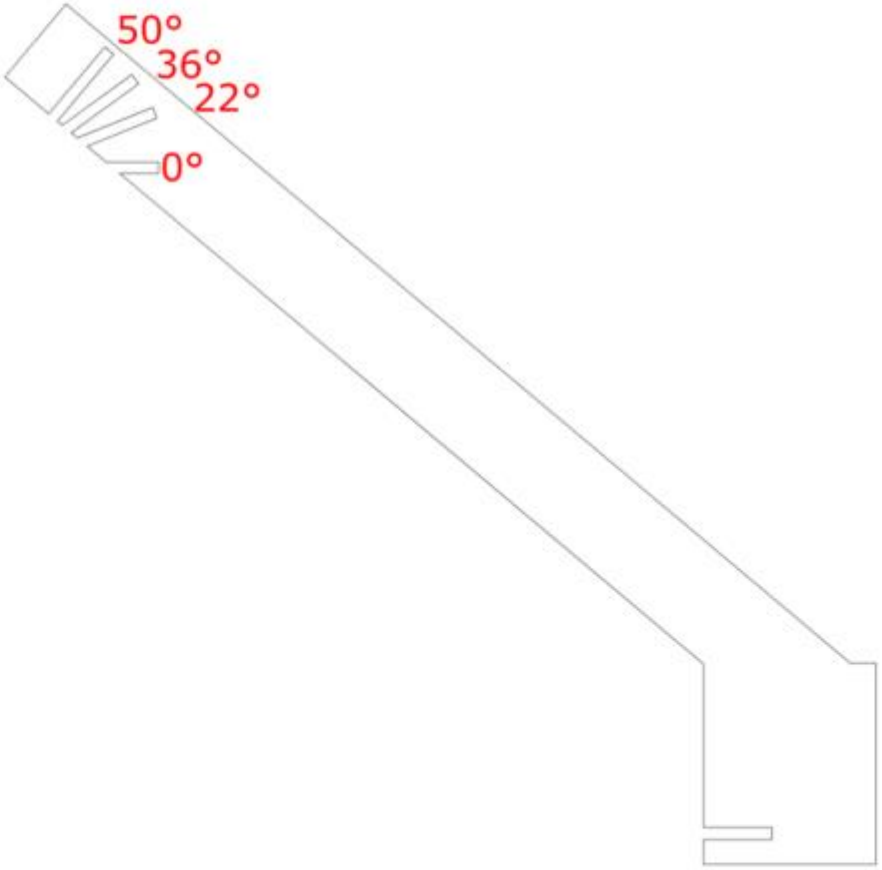
452ms, 25% error
+55ms

Not really

↓ slower but fewer errors (but error difference is very small)

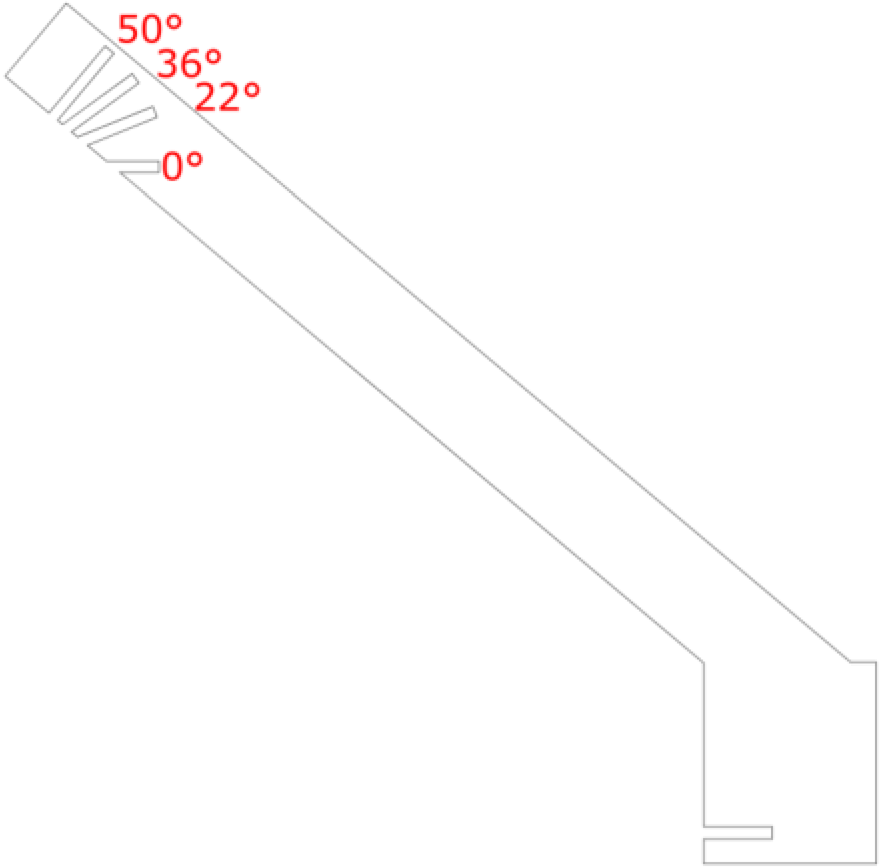
330ms, 27% error
+12ms

Exp 3: Impact of viewing angle



Exp 3: Results

- No evidence of a difference for bar charts
- Radial charts slower & more error at 0°
  but diffs are practically small



What did we learn about smartwatch visualizations?

- Simple tasks can be quickly done (<500ms) even for many dimensions with bars/donuts
- Analog watchface distracts only slightly
- The angle matters only slightly

Conclusion: That's good news!

Micro Visualizations* have a lot of potential for smartwatches

Use them!

**"micro visualizations are small-scale visualizations that fit roughly into foveal vision"*

MOTION

Situated and Embedded Data Representation

People are often moving when looking at situated visualizations

What do we know about how to design visualizations under motion?

ALMOST NOTHING ☹

ALMOST NOTHING ☺

Visualization in Motion

Visualizations in motion are visual data representations used in contexts that exhibit **relative motion** between a **viewer** and an **entire** visualization

Visualizations in Motion

Viewer

Visualization

	Stationary
Stationary	Desktops

Visualizations in Motion

Viewer

Visualization

	Stationary	Moving
Stationary	Desktops	AR / VR Wall Displays Data Physicalization
Moving	AR / VR Video Tracking User Interaction	AR / VR Wearables Mobile DataVis

Research Agenda

Building empirical foundations regarding the impact of…

- Characteristics of Motion
- Situation, context, design
- Spatial relationships
- Technology

IEEE TVCG SUBMISSION 1

Visualization in Motion: A Research Agenda and Two Evaluations

Lijie Yao, Anastasia Bezerianos, Romain Vuillemot, and Petra Isenberg

Moving visualization & stationary viewer. Stationary visualization & moving viewer. Moving visualization & moving viewer.

Fig. 1: Visualization scenarios that involve different types of relative movement between viewers and visualization: (a): 0 A.D. game characters with attached health meters, (b): an augmented basketball match from the tool Clipper CourtVision. (c): a walkable visualization of the general organization of scholars at ENAC in France [71], [72]. (d): an on-street bar chart that can be driven or walked by created by the *Respect New Haven* activist group. (e): a runner looking at her fitness data. (f): a person checking financial charts on her phone while walking to a meeting. *Image permissions are listed in the acknowledgments.*

Abstract—We contribute a research agenda for *visualization in motion* and two experiments to understand how well viewers can read data from moving visualizations. We define visualizations in motion as visual data representations that are used in contexts that exhibit relative motion between a viewer and an entire visualization. Sports analytics, video games, wearable devices, or data physicalizations are example contexts that involve different types of relative motion between a viewer and a visualization. To analyze the opportunities and challenges for designing *visualization in motion*, we show example scenarios and outline a first research agenda. Motivated primarily by the prevalence of and opportunities for visualizations in sports and video games we investigate the impact of two important characteristics of motion outlined in our research agenda—speed and trajectory on a stationary viewer's ability to read data from moving donut and bar charts. We found that increasing speed and trajectory complexity did negatively affect accuracy of reading values from the charts and that bar charts were more negatively impacted. In practice, however, this impact was small: both charts were still read fairly accurately.

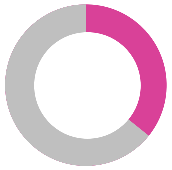
Index Terms—Visualization, visualization in motion, perception, research agenda, movement, motion.

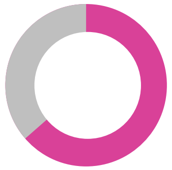
IEEE TVCG, 2022

ANR Grant Ember

Specific Research Questions

How accurately can people read visualization under motion?





Experiment: Part 1

Tell us at what percentage (%) the **red** slice had:

Please enter your answer here | Please give an answer

Visualization in Motion

Speed

Trajectory

01

Motion factors matter

Both speed and trajectory have an impact on the readability of moving simple charts

Visualization in Motion

Speed

Trajectory

Speed and trajectory impact

Higher speed and irregular trajectories generally lead to more errors

02

Visualization in Motion

Speed

Trajectory

03

Can get reliable information

People can read close to exact answers and got reliable information from moving charts

Visualization in Motion

Speed

Trajectory

Donut chart would be a better choice

Participants' performance was slightly worse on bar chart

04

Turn Left
20km/h
15.30
11:45
16:13
37 Km/h
14:27
132
48
02:42
17.4km
19.3km/h
42W

What did we learn about smartwatch visualizations?

- Ideation:
  - Context matters, time matters, bespoke visualizations
- Current practices:
  - Health data of primary interest
  - Generally “low” external complexity
- Perception:
  - People can read vis quickly under motion and in small size

Many untapped opportunities for visualizations on wearables

Summary

Methodologies

Visualization in Motion

Mobile Data Visualization

In-situ and quick information needs

General audiences

ubiquitous visualization

Ubiquitous settings

Empower the general public to use / understand data

Advance scientific knowledge

Establish new research directions

Ubiquitous Visualization

PERSONAL VISUALIZATION

IMMERSIVE ANALYTICS

SITUATED DATA VISUALIZATION

MOBILE VISUALIZATION

should we care about the latest and greatest display technology…

HOW IMPORTANT IS DISPLAY TECHNOLOGY TO US?

http://pixabay.com/en/technology-informatics-computers-298256/

should we care about the latest and greatest display technology…

ABSOLUTELY

http://pixabay.com/en/technology-informatics-computers-298256/

Together we can shape…

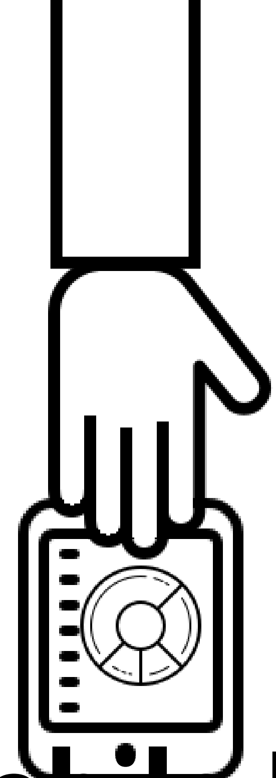
WHAT THE FUTURE OF DATA EXPERIENCES WILL BE LIKE!

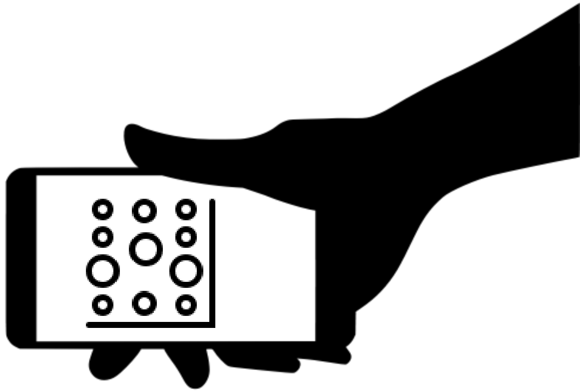
http://pixabay.com/en/technology-informatics-computers-298256/

we need to empower people to…

UNDERSTAND DATA
TO NAVIGATE THE(IR) WORLD

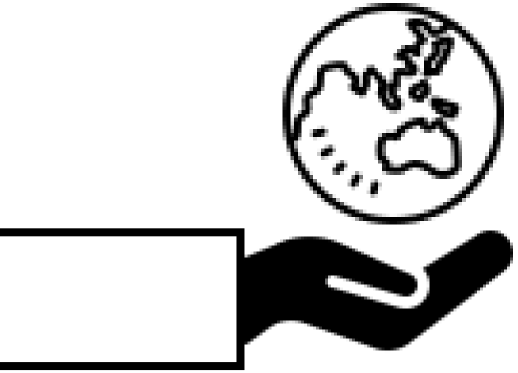
http://photos.jdhancock.com/photo/2012-06-14-051230-universal-hulk.html

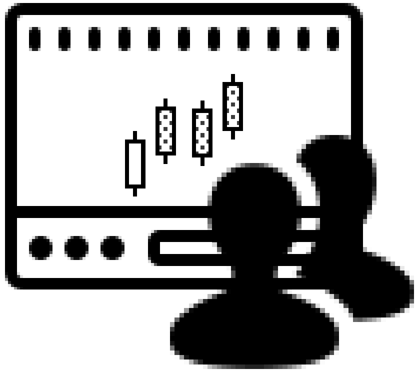




Visualization for Mobile Devices & Embedded Experiences

Petra Isenberg
@dr_pi petra.isenberg@inria.fr





Aviz Visual Analytics Project

Inria

université PARIS-SACLAY

https://icons8.com/