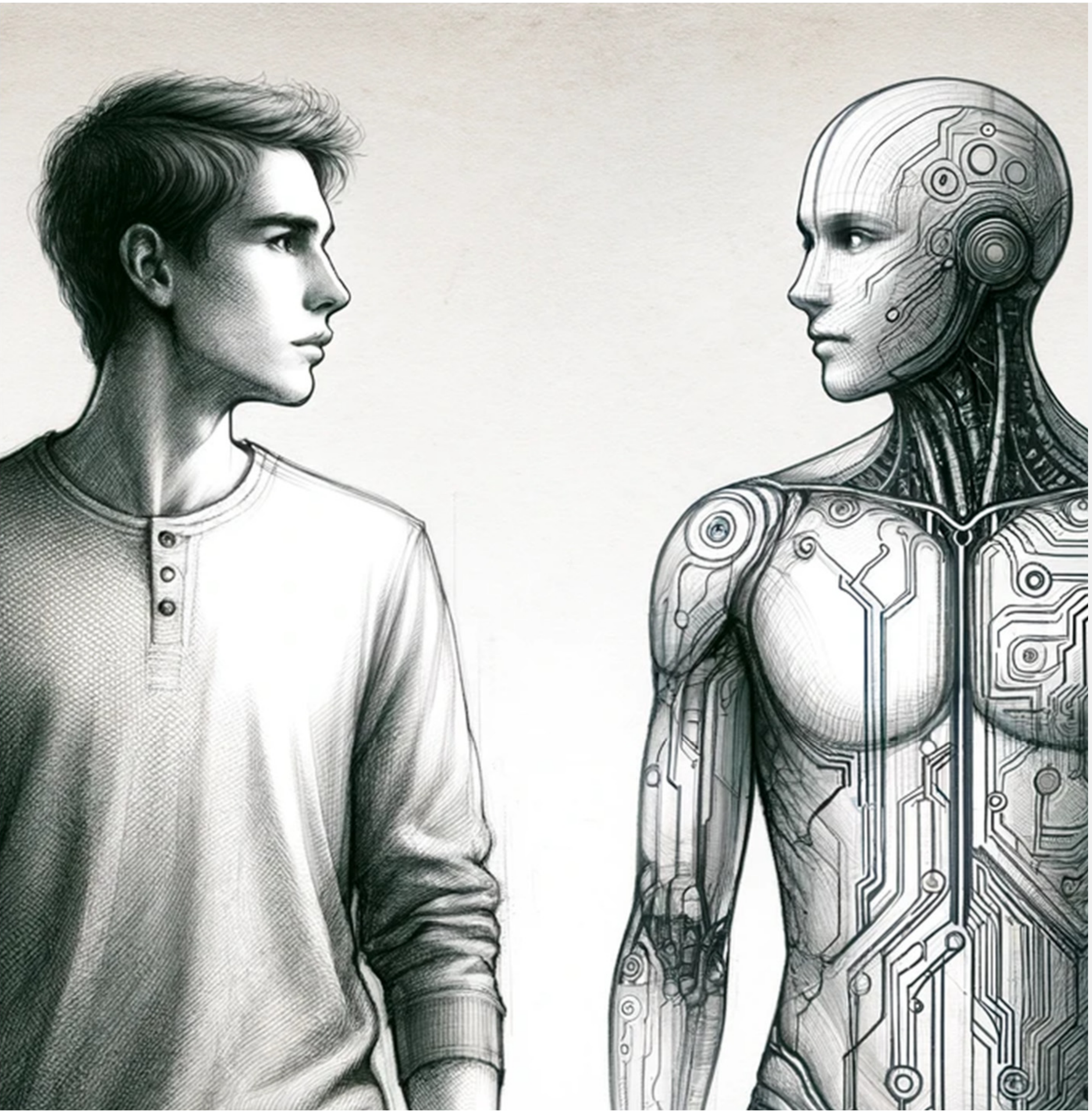
The Predictable Side of Unpredictable Humans

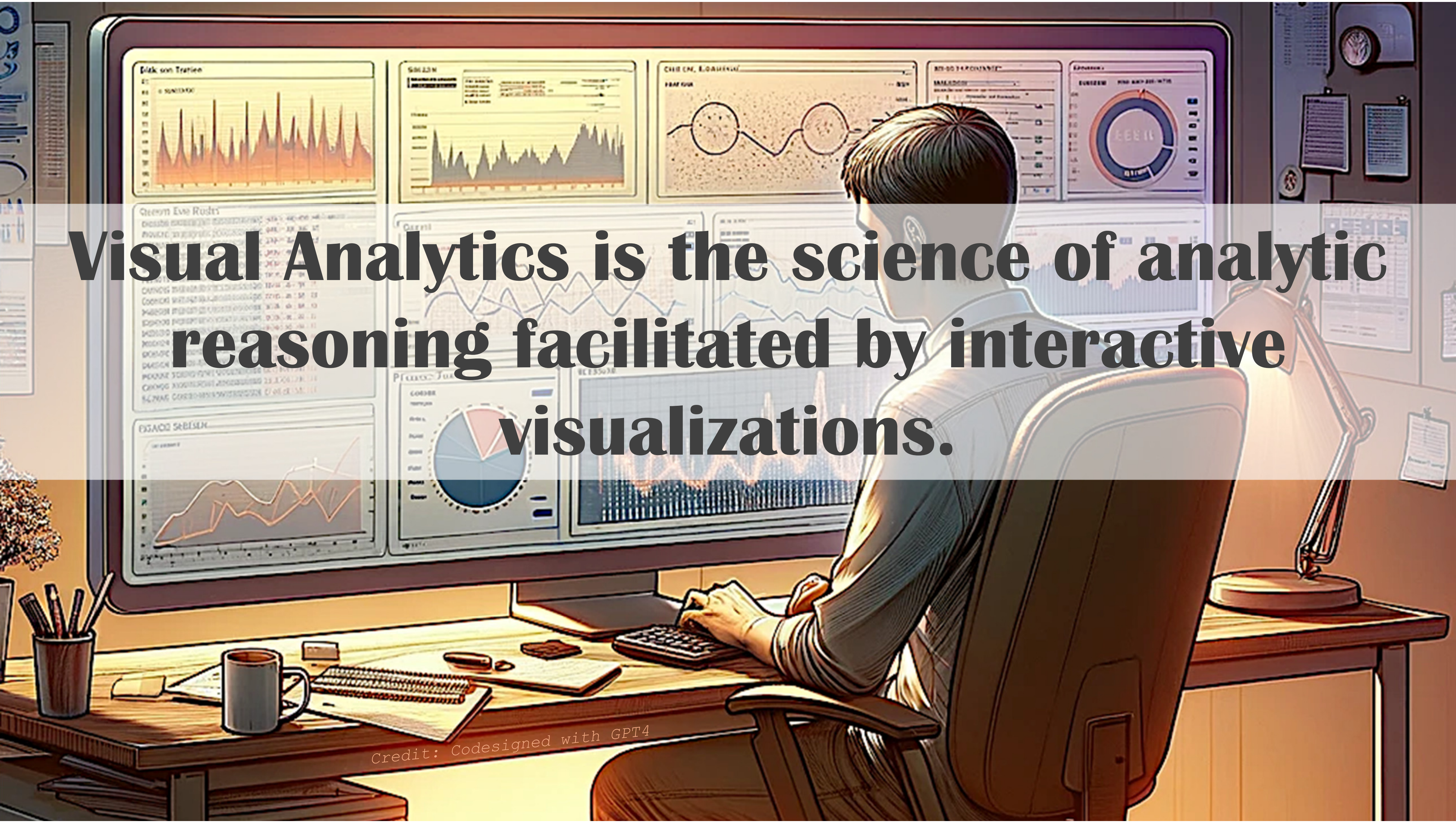
Alvitta Ottley

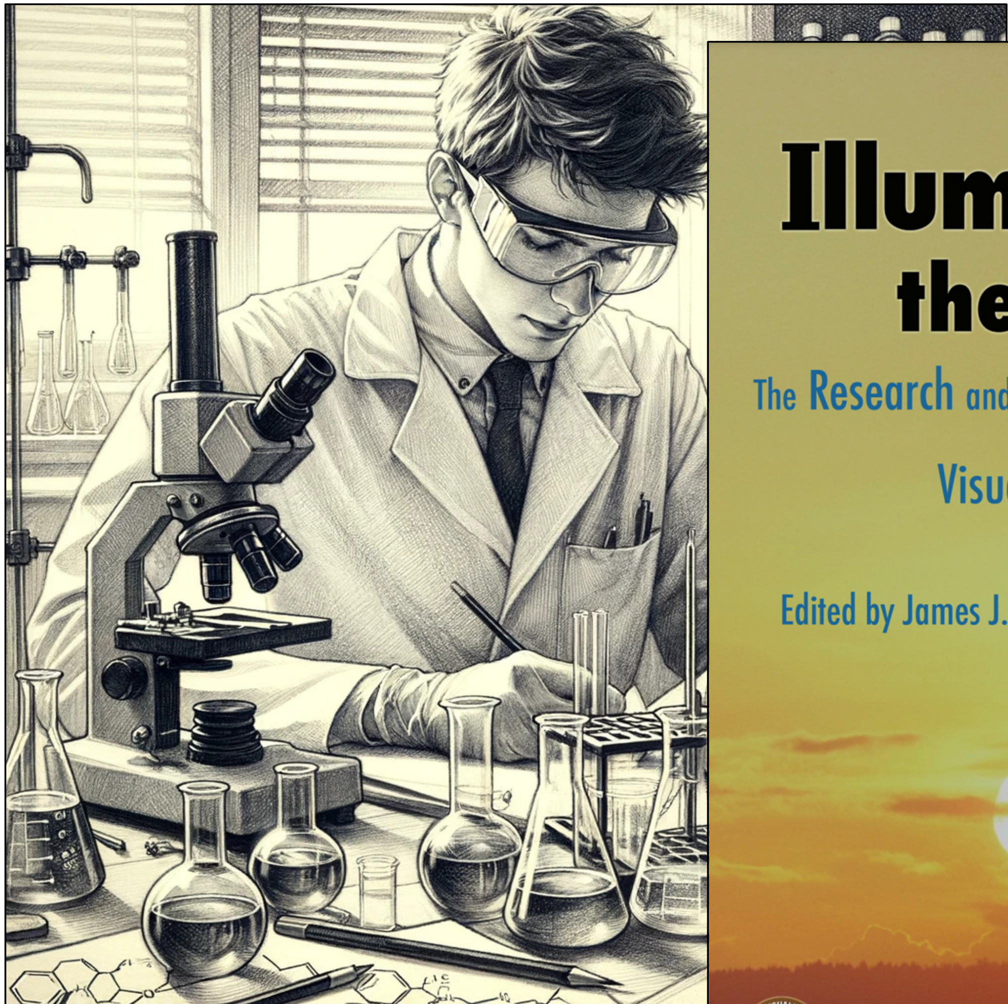
VIBE Visualization Interaction and Behavior Exploration

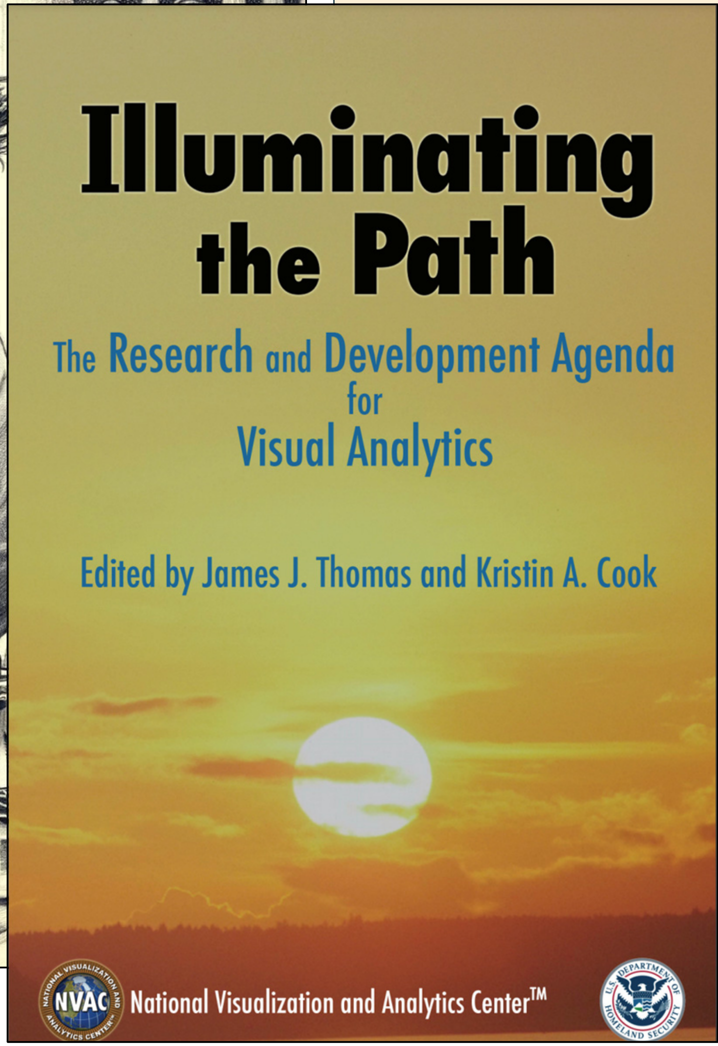
http://visualdata.wustl.edu/



Is it possible for an AI to collaborate in visual analytics, understanding and predicting our behaviors to enhance our analytical capabilities?


Visual Analytics is the science of analytic reasoning facilitated by interactive visualizations.
Credit: Codesigned with GPT4




Illuminating the Path
The Research and Development Agenda for Visual Analytics
Edited by James J. Thomas and Kristin A. Cook
NVAC
National Visualization and Analytics Center™
U.S. Department of Homeland Security

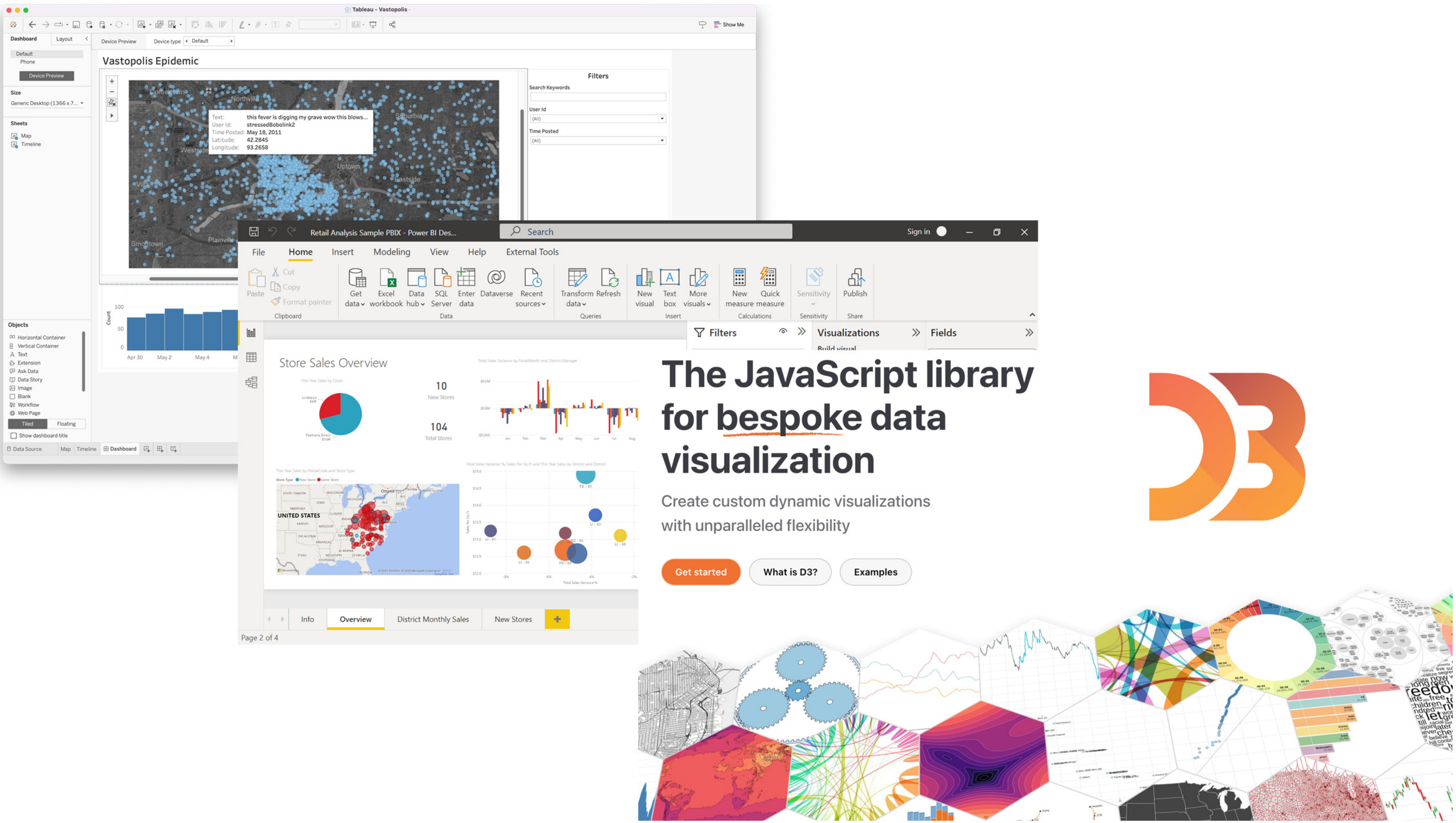
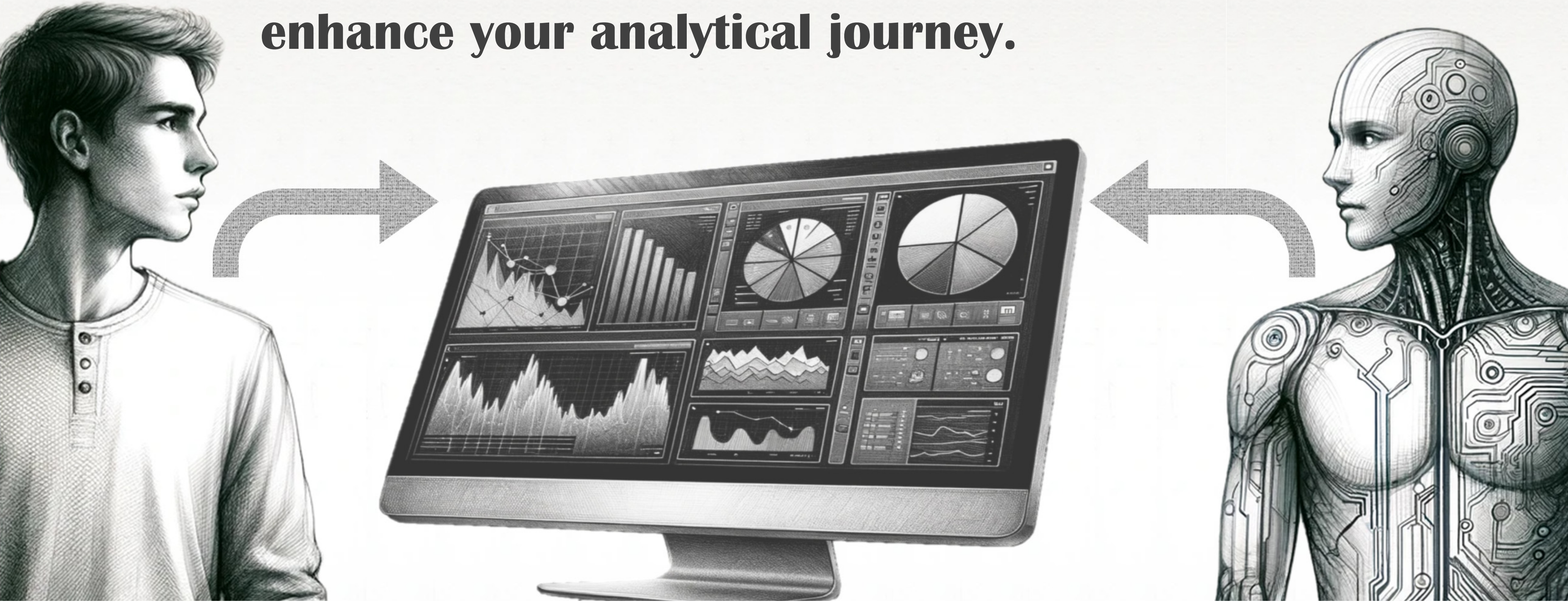


Tableau - Vastopolis
Vastopolis Epidemic
Filters
Search Keywords
User Id
Time Posted
Retail Analysis Sample PBIX - Power BI Des...
Search
File
Home
Insert
Modeling
View
Help
External Tools
Filters
Visualizations
Fields
Store Sales Overview
10
104
Info
Overview
District Monthly Sales
New Stores
Page 2 of 4
The JavaScript library for bespoke data visualization
Create custom dynamic visualizations with unparalleled flexibility
Get started
What is D3?
Examples


Credit: Codesigned with GPT4

Credit: Codesigned with GPT4

It's not just about making predictions but about understanding the context of your queries, the nuances of your exploration, and adapting to enhance your analytical journey.



Challenge 1
Predict the unpredictable user.
How do we quietly observe and
learn from our actions?

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Challenge 2
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Challenge 3
Develop new theoretical models that acknowledge the collaborative potential of AI. What are the ramifications?

Challenge 1
Predict the unpredictable user.
How do we quietly observe and
learn from our actions?

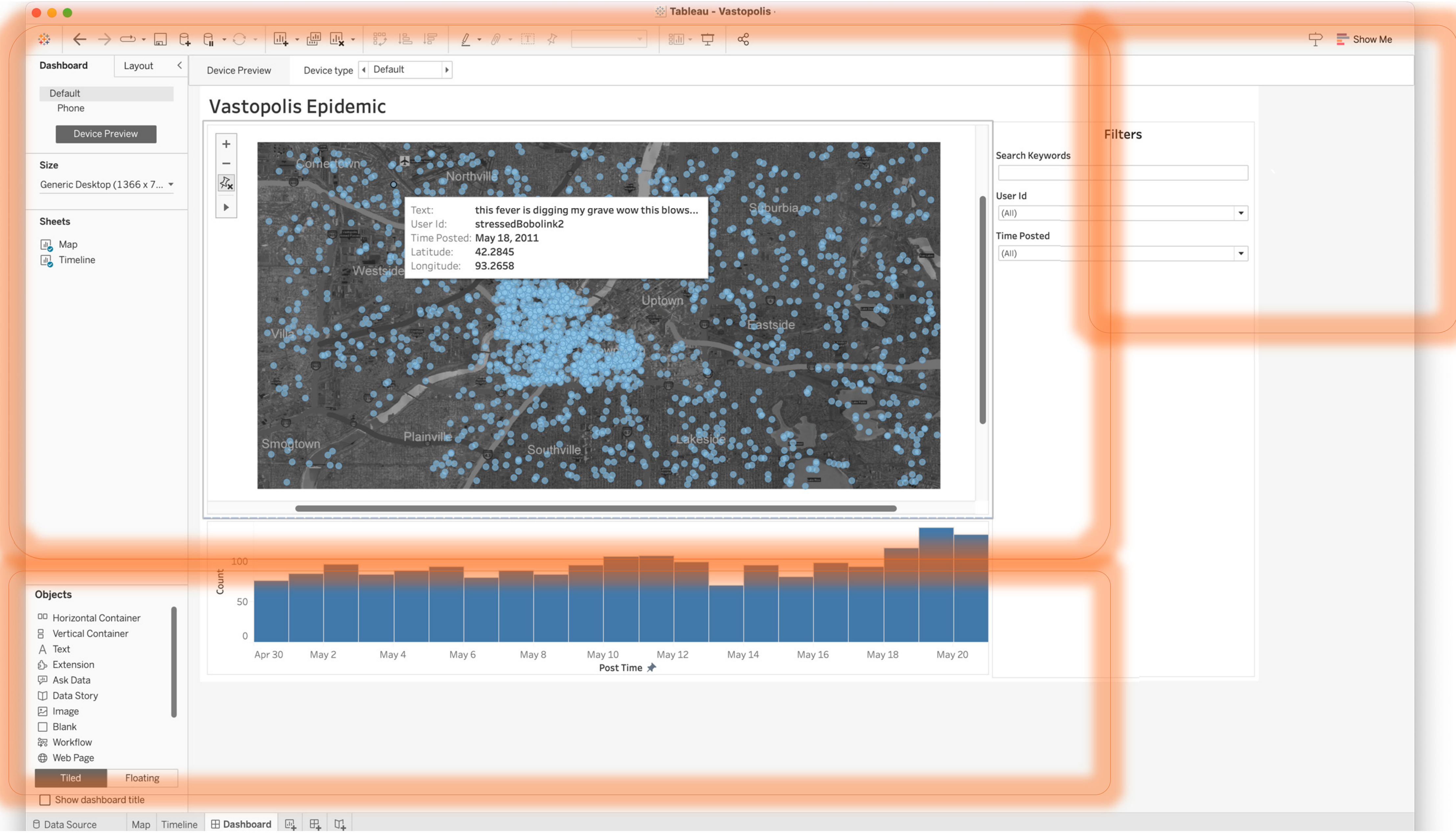

Tableau - Vastopolis
Show Me
Dashboard
Layout
Device Preview
Device type
Default
Default
Phone
Device Preview
Size
Generic Desktop (1366 x 7...
Sheets
Map
Timeline
Vastopolis Epidemic
Filters
Search Keywords
User Id
(All)
Time Posted
(All)
Text: this fever is digging my grave wow this blows...
User Id: stressedBobolink2
Time Posted: May 18, 2011
Latitude: 42.2845
Longitude: 93.2658
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Suburbia
Westside
Uptown
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Southville
Lakeside
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May 12
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May 16
May 18
May 20
Post Time
Objects
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Vertical Container
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Extension
Ask Data
Data Story
Image
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Workflow
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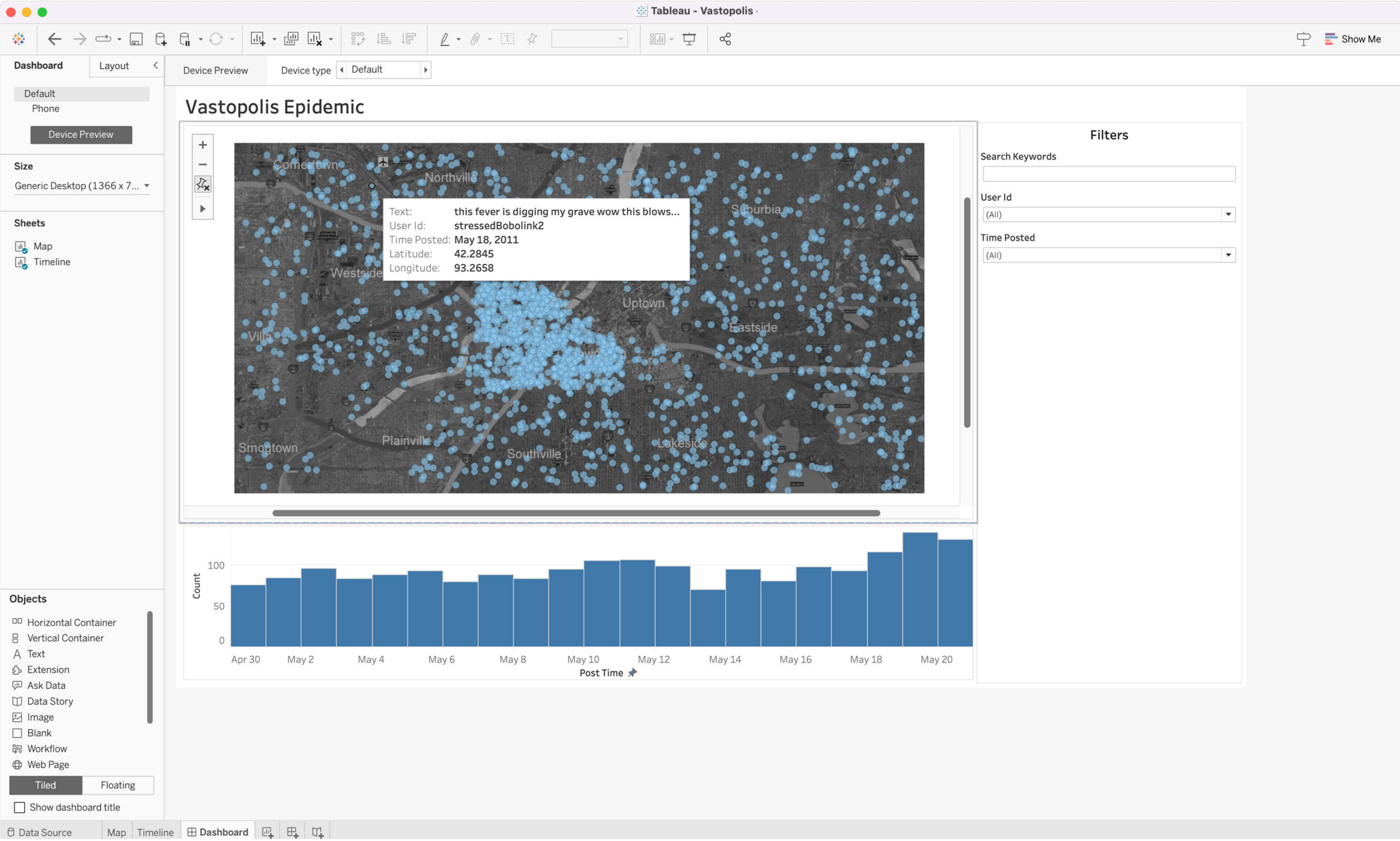
Tiled
Floating
Show dashboard title
Data Source
Map
Timeline
Dashboard



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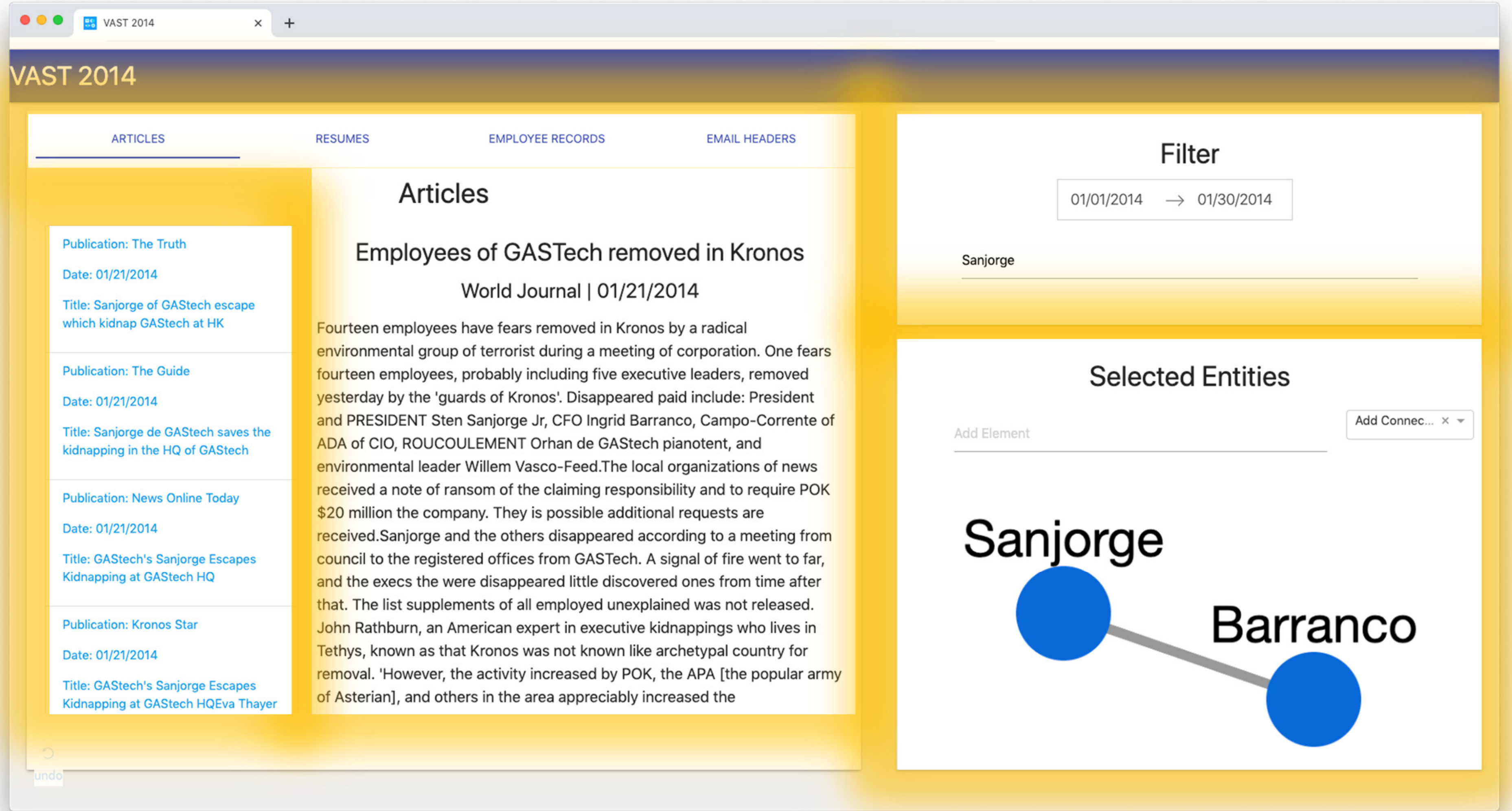
Timeline
Dashboard

NC STATE UNIVERSITY

LAS

Laboratory for Analytic Sciences

Collaborate. Innovate. Transform.


VAST 2014
VAST 2014
ARTICLES
RESUMES
EMPLOYEE RECORDS
EMAIL HEADERS
Publication: The Truth
Date: 01/21/2014
Title: Sanjorge of GAStech escape which kidnap GAStech at HK
Publication: The Guide
Date: 01/21/2014
Title: Sanjorge de GAStech saves the kidnapping in the HQ of GAStech
Publication: News Online Today
Date: 01/21/2014
Title: GAStech's Sanjorge Escapes Kidnapping at GAStech HQ
Publication: Kronos Star
Date: 01/21/2014
Title: GAStech's Sanjorge Escapes Kidnapping at GAStech HQEva Thayer
Articles
Employees of GASTech removed in Kronos
World Journal | 01/21/2014
Fourteen employees have fears removed in Kronos by a radical environmental group of terrorist during a meeting of corporation. One fears fourteen employees, probably including five executive leaders, removed yesterday by the 'guards of Kronos'. Disappeared paid include: President and PRESIDENT Sten Sanjorge Jr, CFO Ingrid Barranco, Campo-Corrente of ADA of CIO, ROUCOULEMENT Orhan de GASTech pianotent, and environmental leader Willem Vasco-Feed.The local organizations of news received a note of ransom of the claiming responsibility and to require POK $20 million the company. They is possible additional requests are received.Sanjorge and the others disappeared according to a meeting from council to the registered offices from GASTech. A signal of fire went to far, and the execs the were disappeared little discovered ones from time after that. The list supplements of all employed unexplained was not released. John Rathburn, an American expert in executive kidnappings who lives in Tethys, known as that Kronos was not known like archetypal country for removal. 'However, the activity increased by POK, the APA [the popular army of Asterian], and others in the area appreciably increased the
undo
Filter
01/01/2014 → 01/30/2014
Sanjorge
Selected Entities
Add Element
Add Connec...
Sanjorge
Barranco

EuroVis 2020
R. S. Laramee, M. Sedlmair, G. E. Marai
(Guest Editors)

Volume 37 (2020), Number 3
STAR – State of The Art Report

Survey on Individual Differences in Visualization

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Abstract

Developments in data visualization research have enabled visualization systems to achieve great general usability and application across a variety of domains. These advancements have improved not only people's understanding of data, but also the general understanding of people themselves, and how they interact with visualization systems. In particular, researchers have gradually come to recognize the deficiency of having one-size-fits-all visualization interfaces, as well as the significance of individual differences in the use of data visualization systems. Unfortunately, the absence of comprehensive surveys of the existing literature impedes the development of this research. In this paper, we review the research perspectives, as well as the personality traits and cognitive abilities, visualizations, tasks, and measures investigated in the existing literature. We aim to provide a detailed summary of existing scholarship, produce evidence-based reviews, and spur future inquiry.

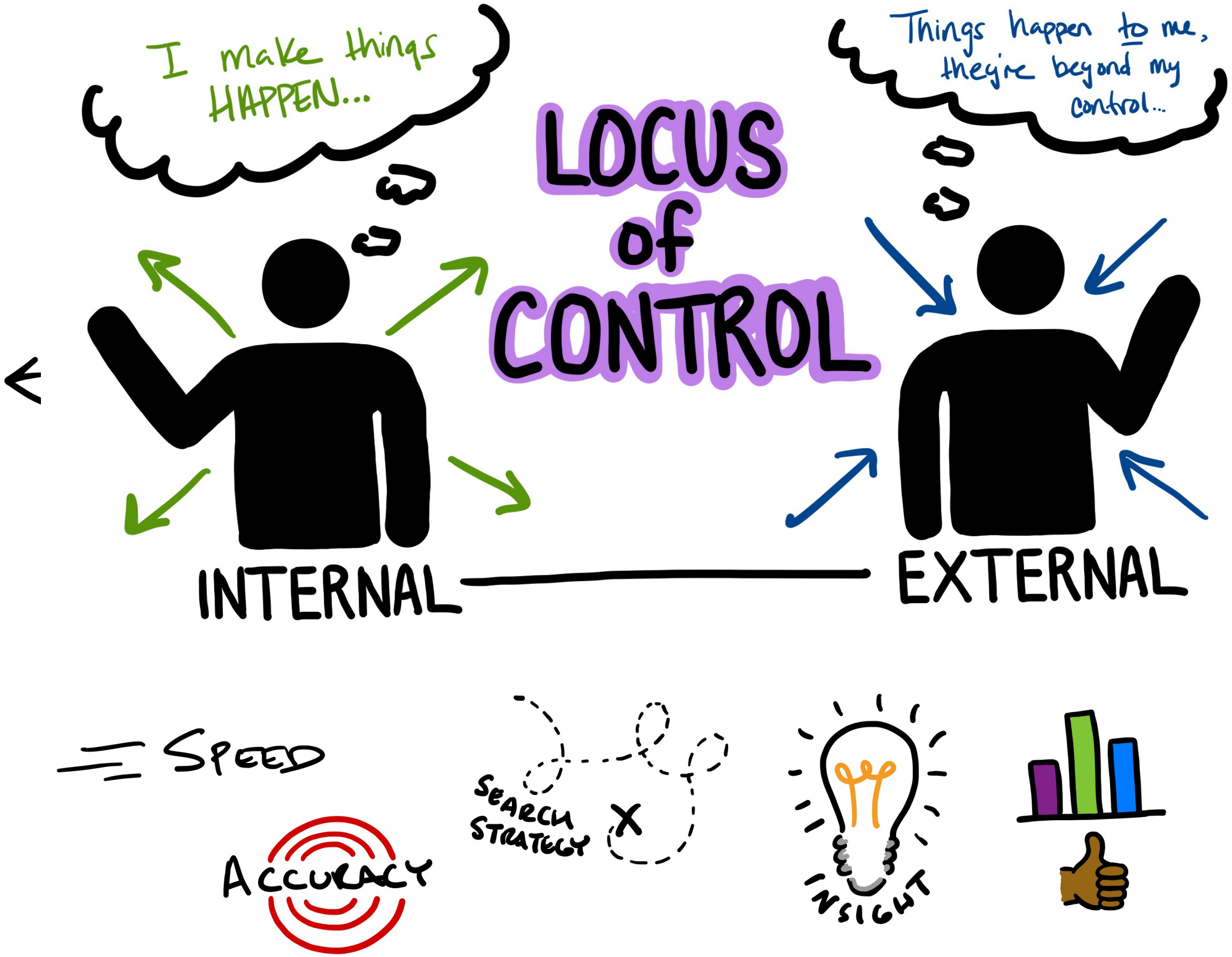
1. Introduction

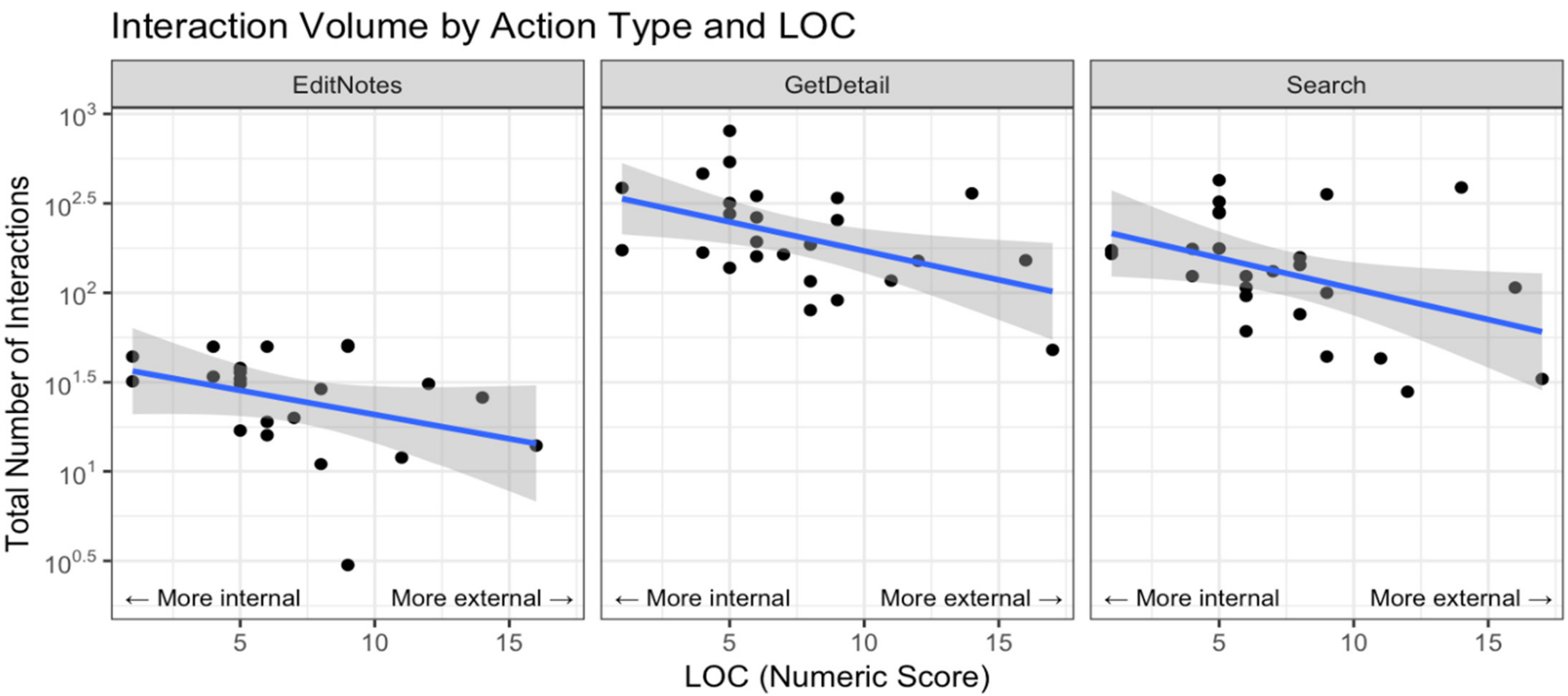
The term *individual differences* refers to individuals' "traits or stable tendencies to respond to certain classes of stimuli or situations in predictable ways" [DW96]. Much of the literature on individual differences has roots in psychology. Psychological research has demonstrated that people with distinct personality types and various cognitive abilities exhibit observable differences in task-solving and behavioral patterns [WB00, Ajz05]. Studies dating back to the late 1920s began by investigating variations in workplace performance [Hul28]. Throughout the intervening century, these findings have been extended to investigate individual characteristics that may predict performance under various conditions.

In the past few decades, the computational sciences have begun to recognize the role individual differences might play in shaping interaction in human-machine systems. For example, Benyon and Murray observed a relationship between *spatial ability* (a metric that measures a person's ability to mentally represent and manipulate two- or three-dimensional objects) and task performance and preferences when using common interaction paradigms such as menus and the command line [BM93]. Nov et al. [NALB13] found that *extraversion* (one's tendency to engage with the external world) and *neuroticism* (a measure of emotional stability) had effects on users' contributions to online discussions, and suggested adaptations to certain visual cues to cater to different personality types. Gajos and Chauncey [GC17] observed that *introverted* people were more likely to use adaptive features in user interfaces as compared to *extraverts*. Orji et al. [ONDM17] showed that *conscientious* participants (a measure of carefulness or diligence) responded well to persuasive strategies such as self-monitoring and feedback in gamified systems. These studies are just a small sample of a large body of work documenting the influence of personality and cognitive ability on interactions with computer interfaces. For more detailed surveys of the literature, see [AA91, Poc91, DW96].

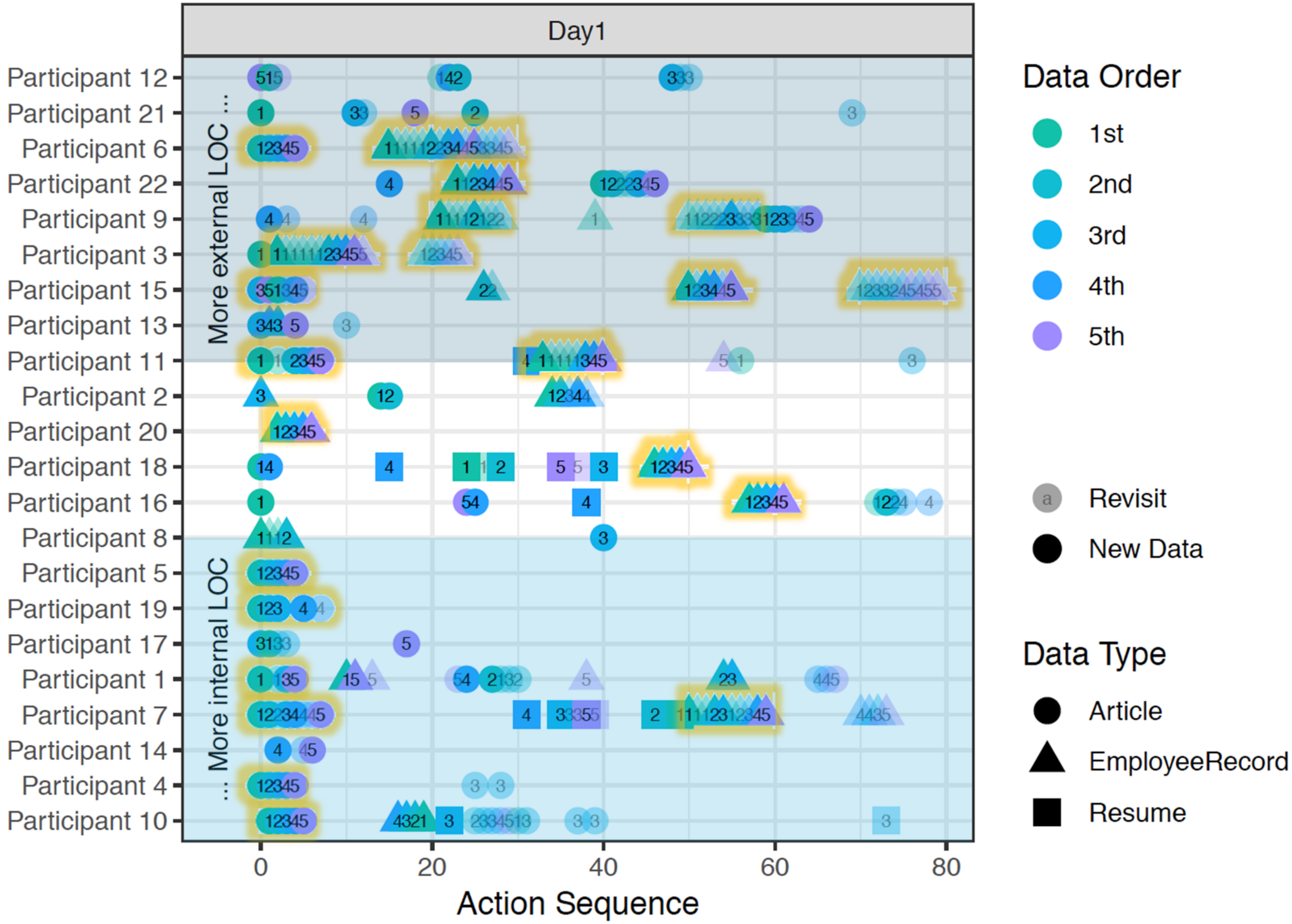
There is a growing interest in extending these findings to the field of data visualization [Yi12, ZOC*12a]. Some posit that knowledge of broad differences between user groups could guide the design, evaluation, or customization of systems [VHW87, ZOC*12a]. Supporting this claim, a cluster of promising research has produced evidence to suggest that individual characteristics, in addition to data mapping and visual encodings, determine the value of a visualization system. These studies have demonstrated that personality traits and cognitive abilities can have substantial impact on task performance [GF10, ZCY*11], usage patterns [BOZ*14, OYC15] and user satisfaction [Kob04]. Building on these findings, others have begun to examine how we might leverage cognitive traits for applications such as user modeling [BOZ*14, OYC15] and adaptive interfaces [LTC19].

In some circumstances, the interaction between individual differences and visualization use may have critical impact on important decision-making processes. Ottley et al. [OPH*15] investigated the impact of visualization on medical decision-making, and found that approximately 50% of the studied population were unsupported by commonly-used visualization tools when making decisions about their medical treatment. Specifically, their study showed that visual aides tended to be most beneficial for people with high *spatial ability*, while those with low *spatial ability* had difficulty interpreting and analyzing the underlying medical data when they were presented with visual representations. Another study by Conati and Maclaren [CM08] found that participants with high *perceptual speed* were less accurate in computing derived values when using radar graphs instead of heatmapped tables for data analysis. A series of studies have shown that *locus of control* (a measure of perceived control over external events) mediates search performance on hierarchical visualizations [GJF10, GF12, ZCY*11, ZOC*12b, OYC15, OCZC15]. These findings underscore the importance of incorporating individual differences into the design pipeline in order to create visualization tools that are broadly usable.



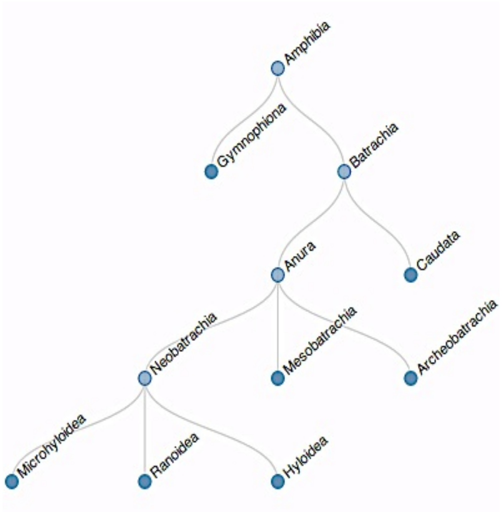


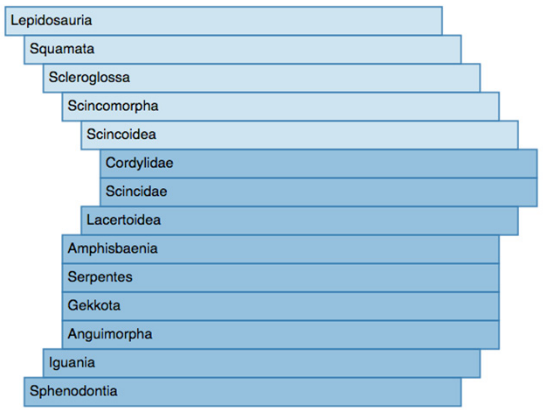
Interaction Volume by Action Type and LOC
EditNotes
GetDetail
Search
Total Number of Interactions
$10^{0.5}$
10^{1}
$10^{1.5}$
10^{2}
$10^{2.5}$
10^{3}
← More internal
More external →
5
10
15
LOC (Numeric Score)

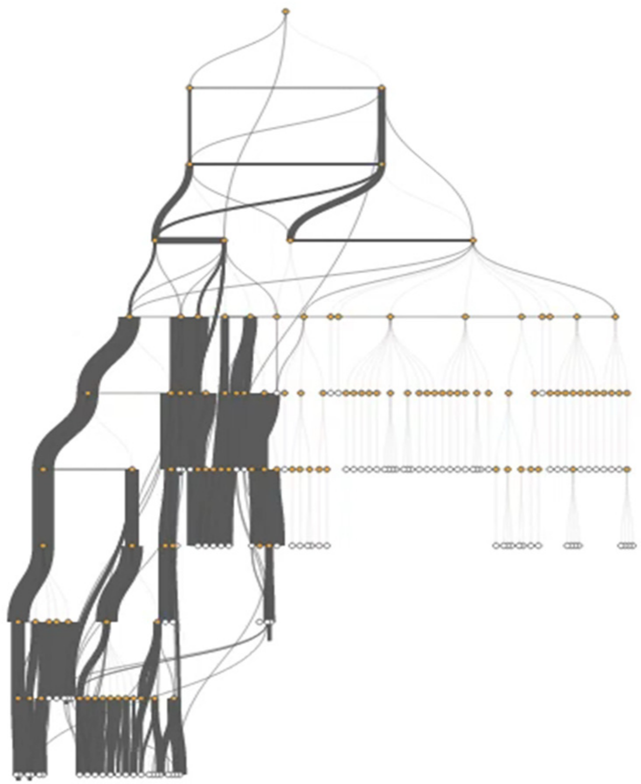


Day1
Participant 12
Participant 21
Participant 6
Participant 22
Participant 9
Participant 3
Participant 15
Participant 13
Participant 11
Participant 2
Participant 20
Participant 18
Participant 16
Participant 8
Participant 5
Participant 19
Participant 17
Participant 1
Participant 7
Participant 14
Participant 4
Participant 10
More external LOC ...
... More internal LOC
0
20
40
60
80
Action Sequence
Data Order
1st
2nd
3rd
4th
5th
Revisit
New Data
Data Type
Article
EmployeeRecord
Resume

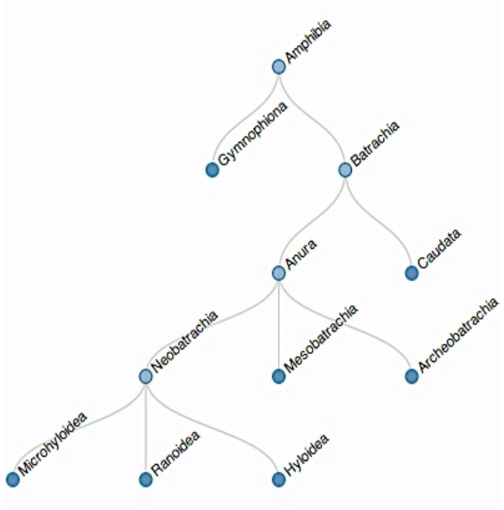
Hierarchical Search Strategies

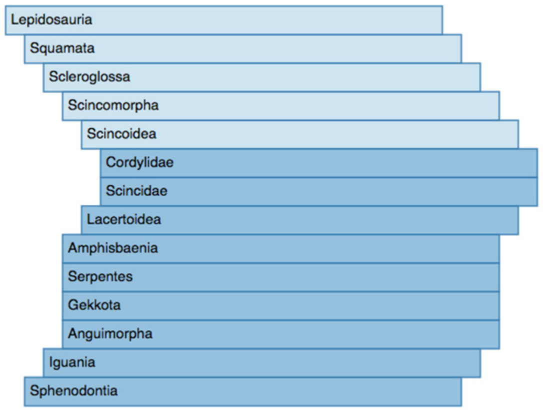


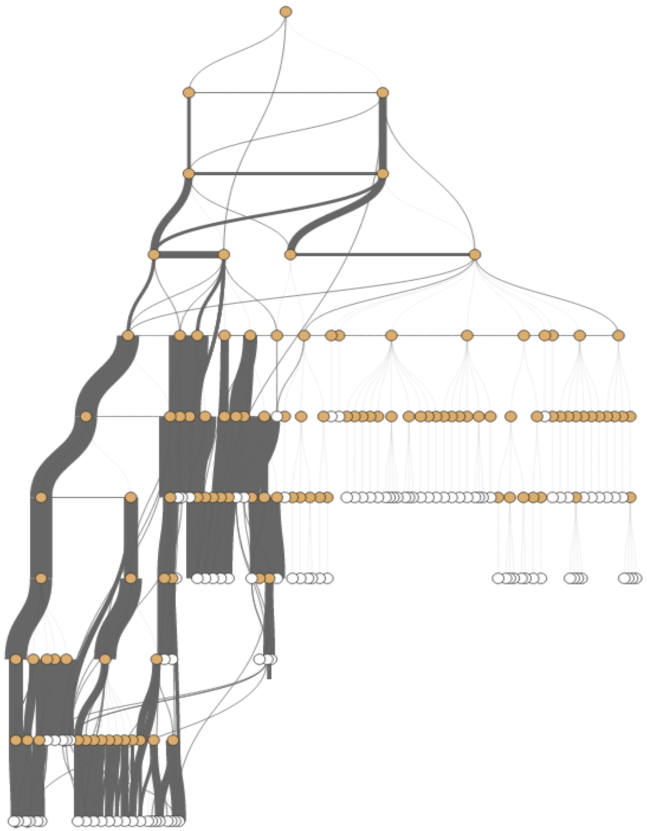


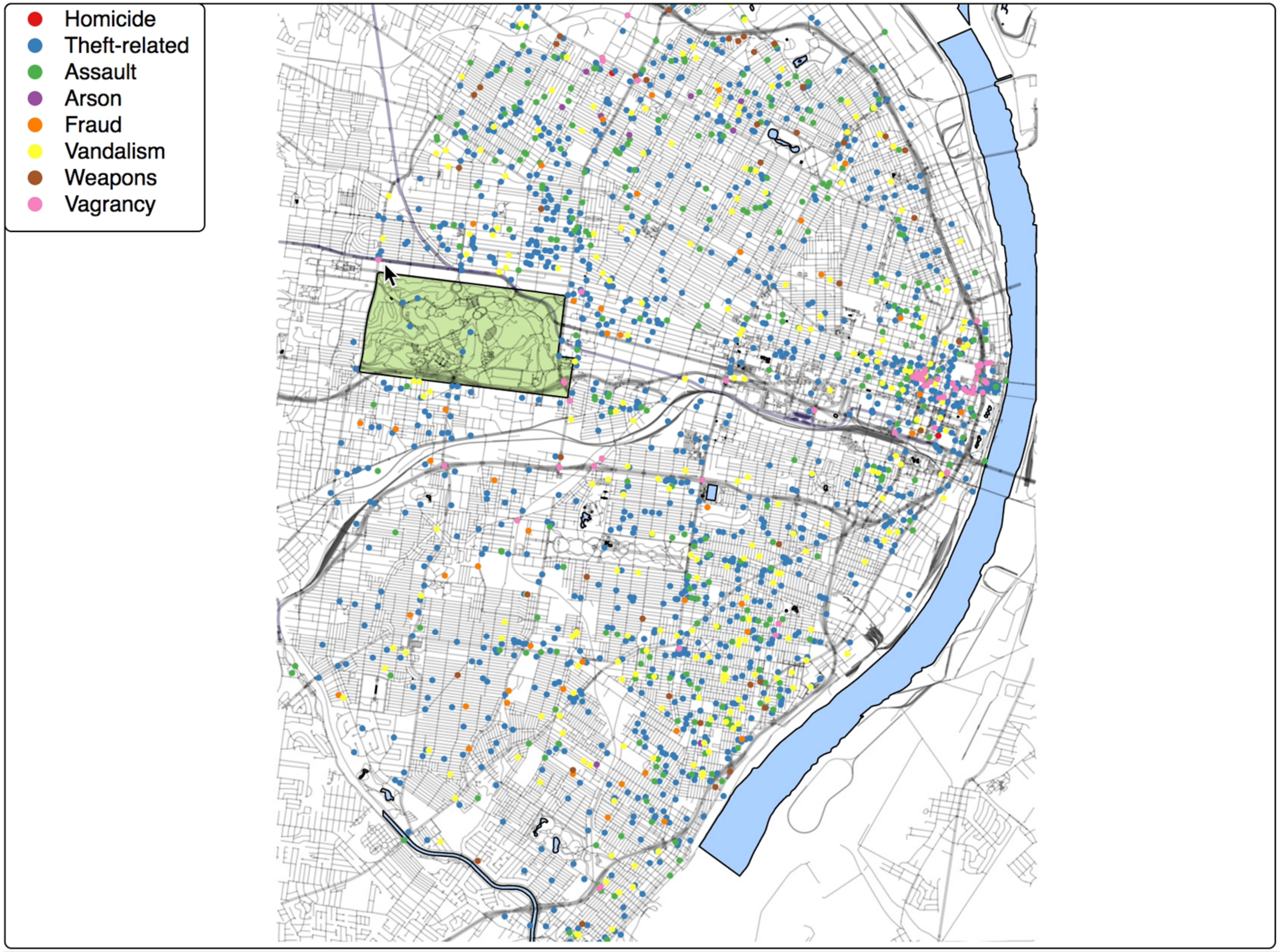


Hierarchical Search Strategies





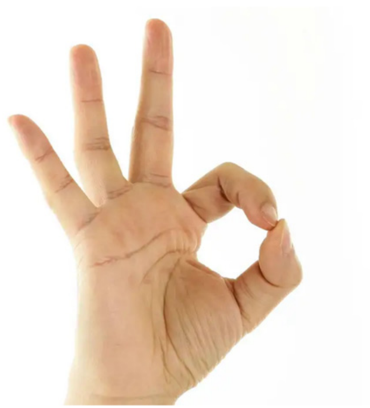



Homicide
Theft-related
Assault
Arson
Fraud
Vandalism
Weapons
Vagrancy

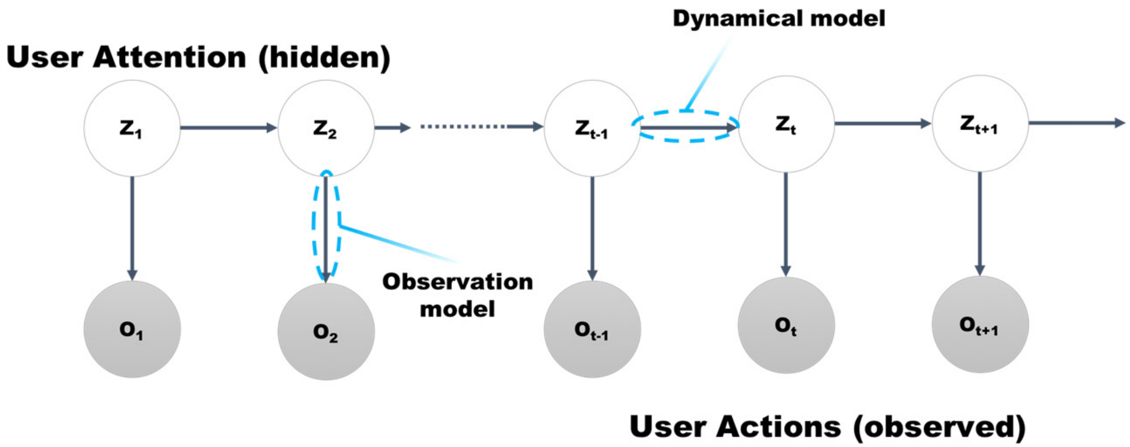
Machine Learning for Time Series

- Samples arrive sequentially
- Sample size is unknown and varies
- Data are not available during training
- Waiting for until time T to accumulate a batch may not be feasible
  - Eliminates recurrent Neural Network (rNN), i.e., long short-term memory network
    - Notoriously difficult to train
    - Require temporal relationships of the past and future to be similar

We use a **hidden Markov model** to represent evolving attention



Applying hidden Markov model to visualizations



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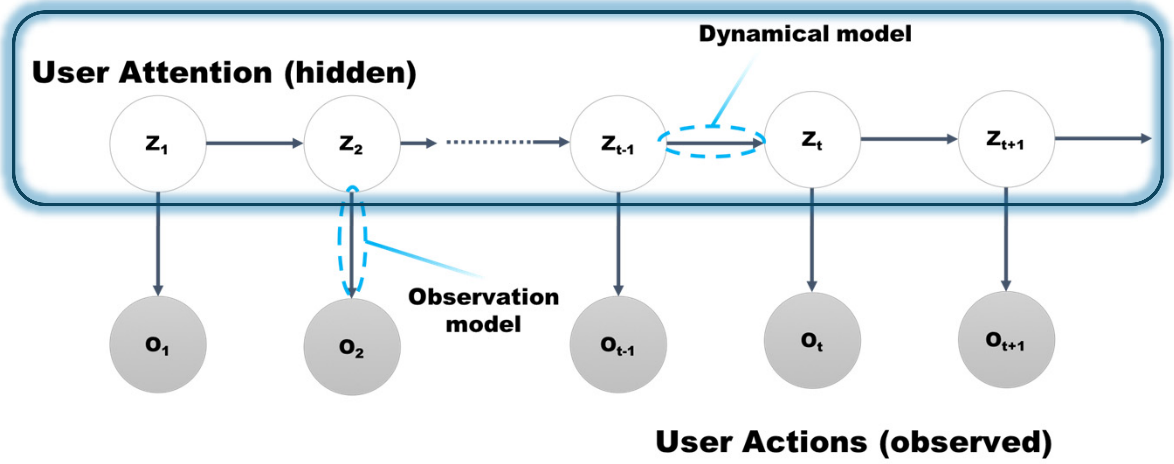
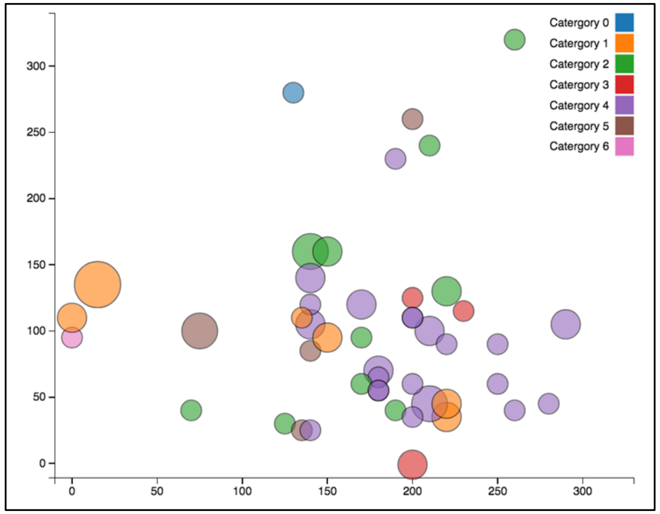


1. Define hidden states
2. Define observations
3. Define dynamical model
4. Define observational model

People attend to visual elements



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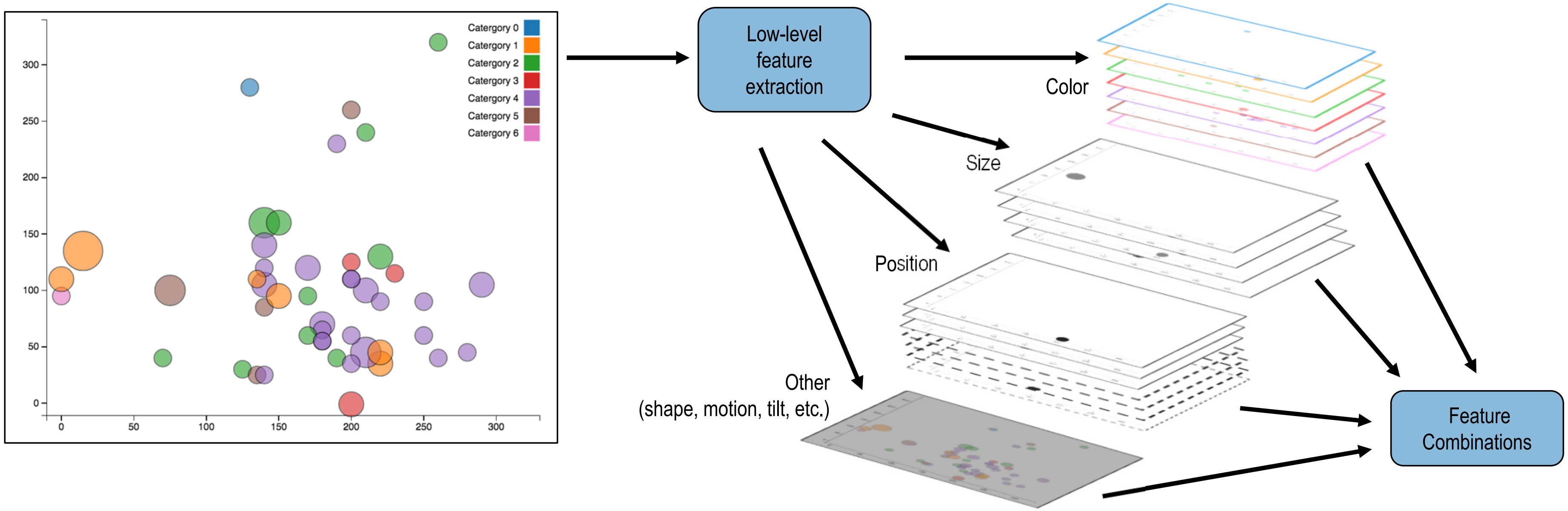
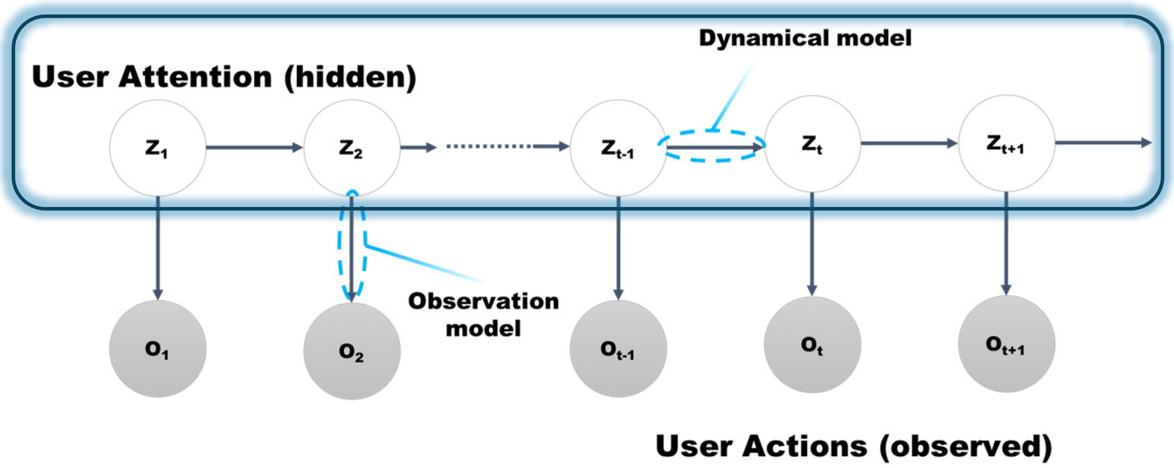


Formal definition of Hidden States



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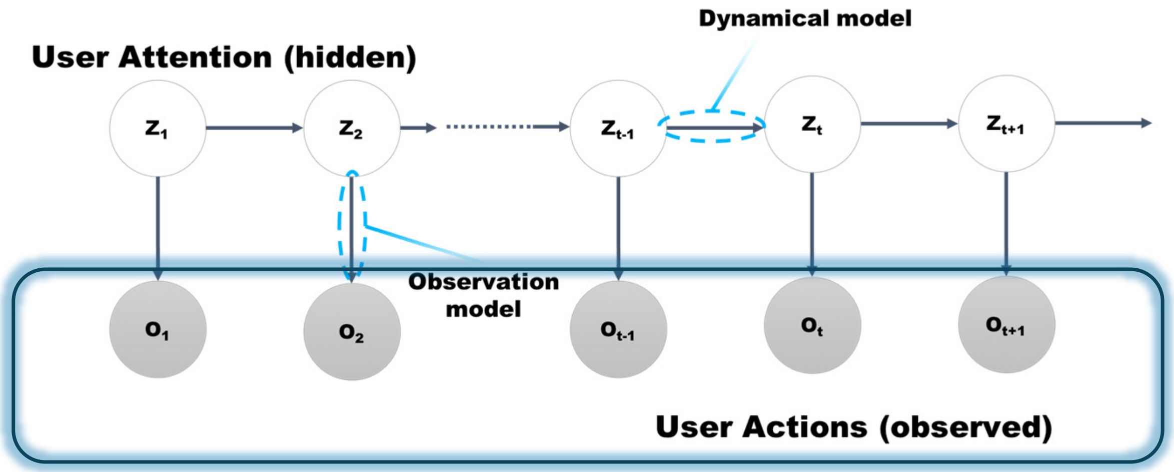
2. Define observations
3. Define dynamical model
4. Define observational model

$$\mathscr{M} = \{f_1, \ldots, f_N\}$$

Mark Space: The set of N visual features extracted from the visualization (e.g., position, size, and color)

Observations



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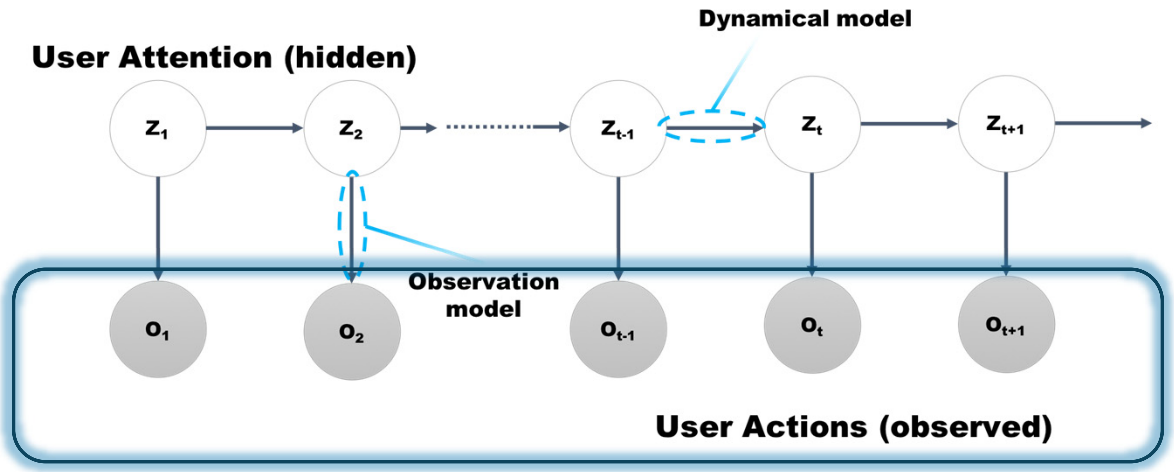
Formal definition of Observations



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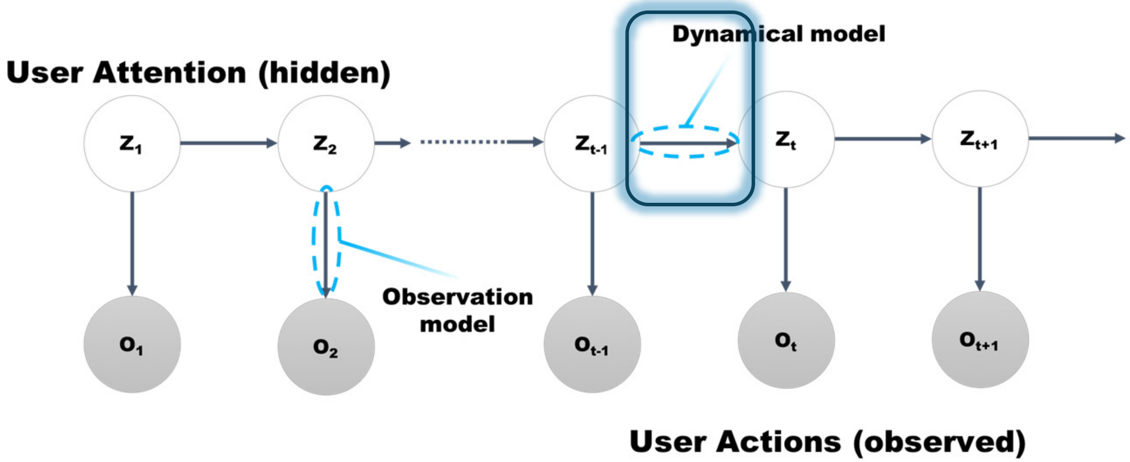
$$o_t = \{f'_1, \ldots, f'_N\}$$

Any user interaction with visual elements (.e.g. mouse click, key stroke, eye gaze, speech, pan, zoom)

Shifts in Attention



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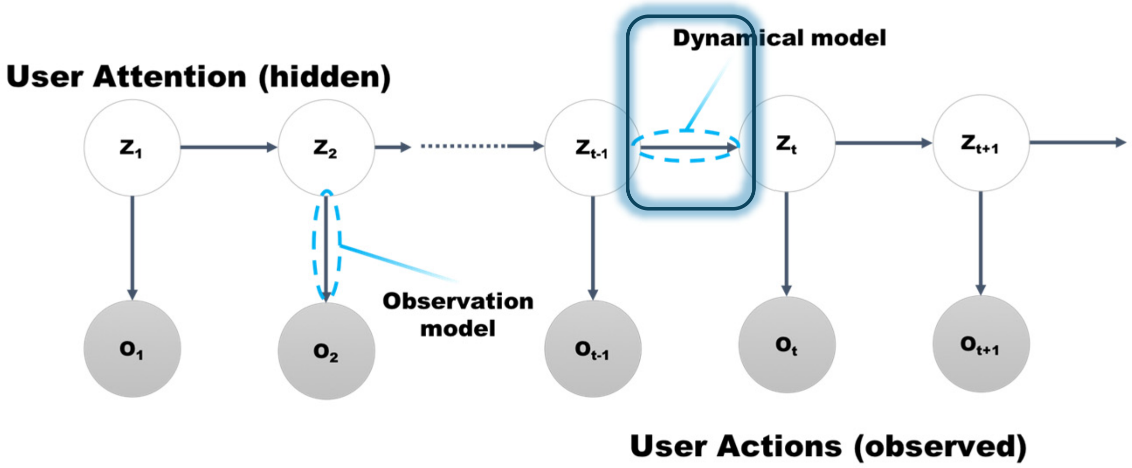
Formal definition of Shifts in Attention



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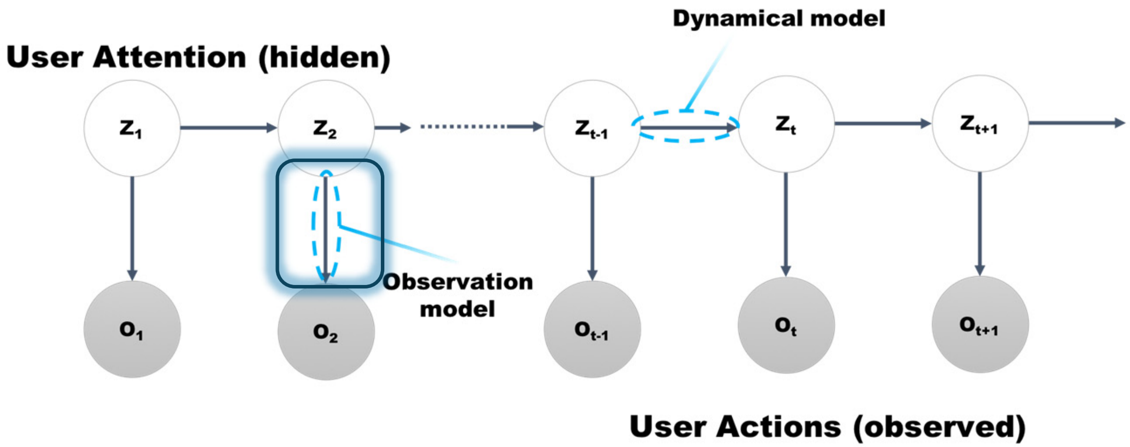
$$z_{t+1} = z_t + \varepsilon,$$

Observational Model



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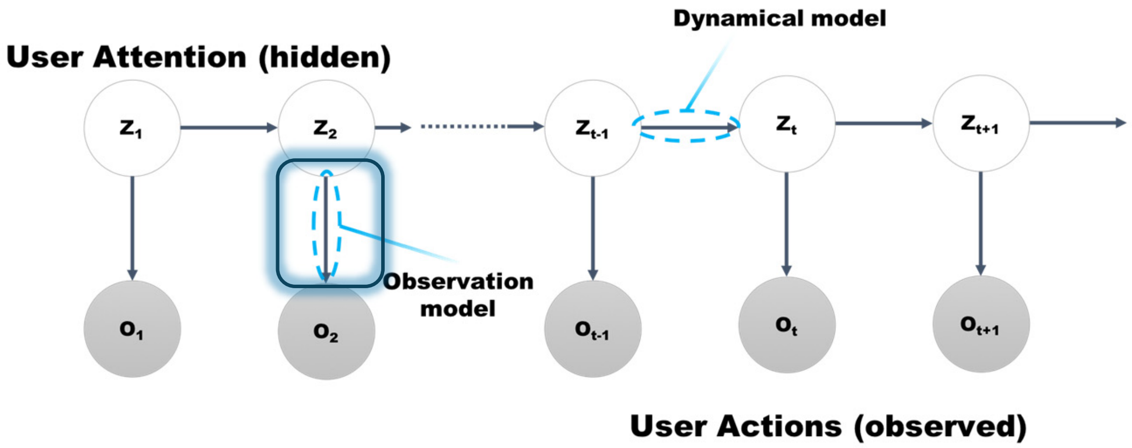
Formal definition of Observational Model



1. Define hidden states
2. Define observations
3. Define dynamical model
4. Define observational model

Loosely translates to "people will interact with elements related to their hidden attention space."

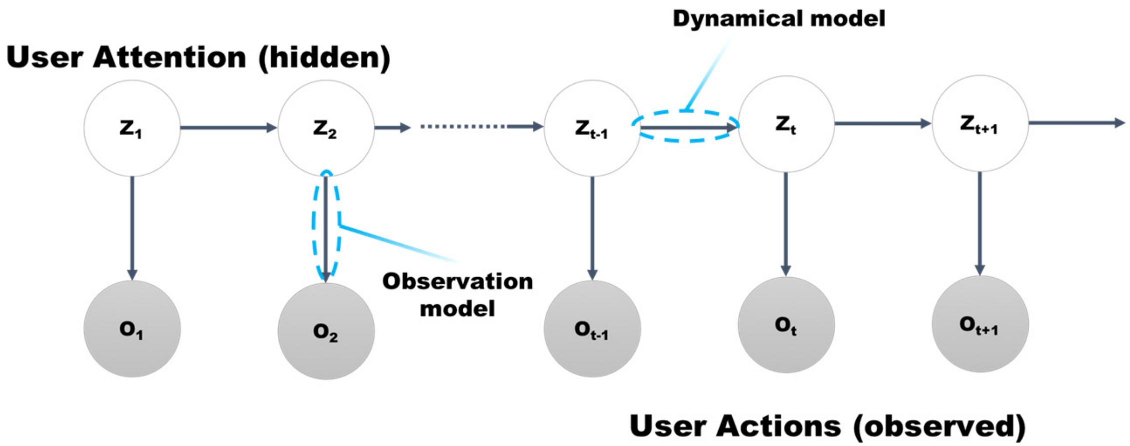
One additional component…

Bias Vector

- It is useful to consider bias when modeling attention
- Attention at time t+1 is similar to attention at time t

$$bias\ \ vector\ \ \boldsymbol{\pi} = [\boldsymbol{\pi}(f_1), \ldots, \boldsymbol{\pi}(f_N)]$$

Applying hidden Markov model to visualizations



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2. Define observations
3. Define dynamical model
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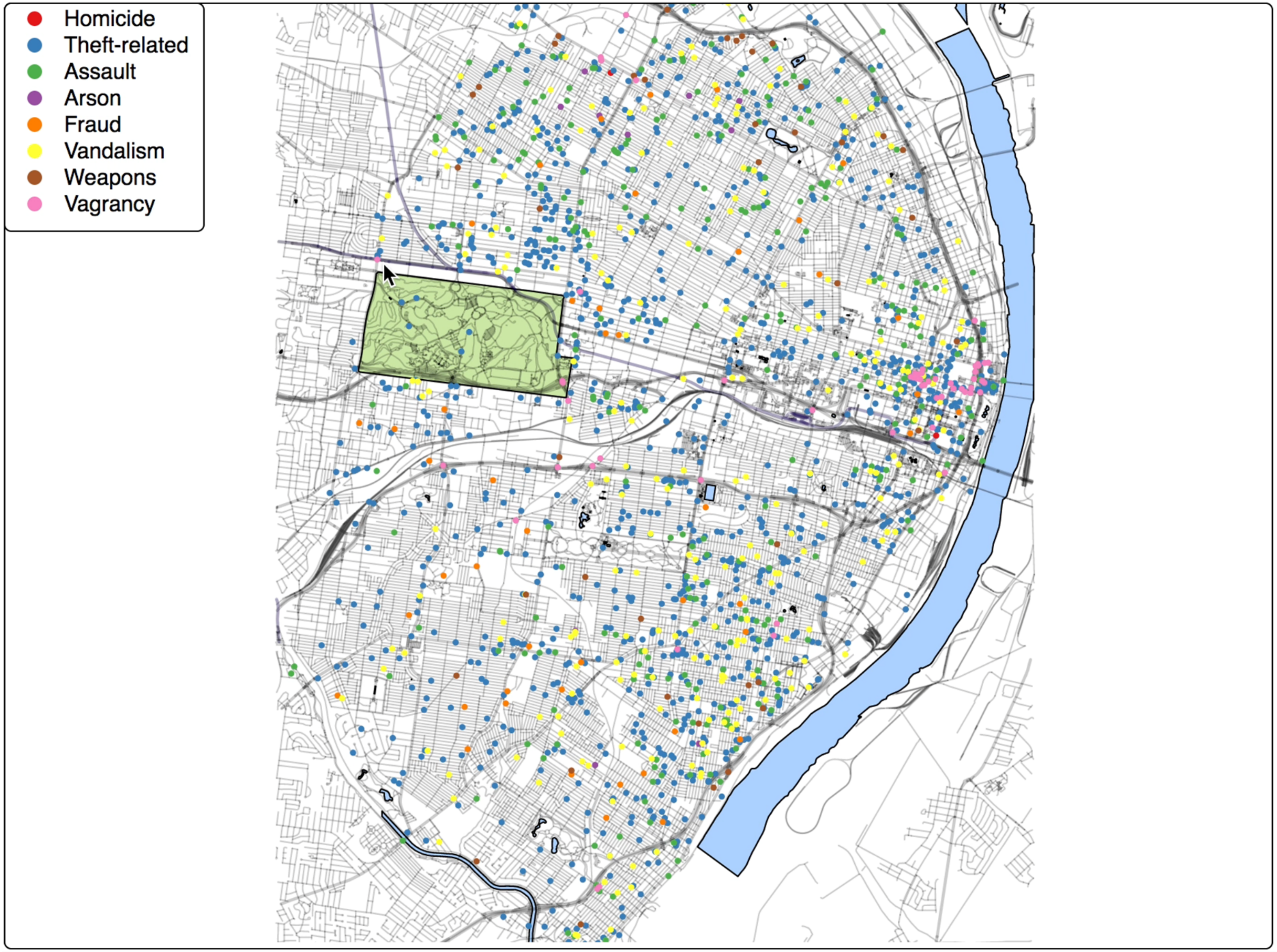
Making predictions


Homicide
Theft-related
Assault
Arson
Fraud
Vandalism
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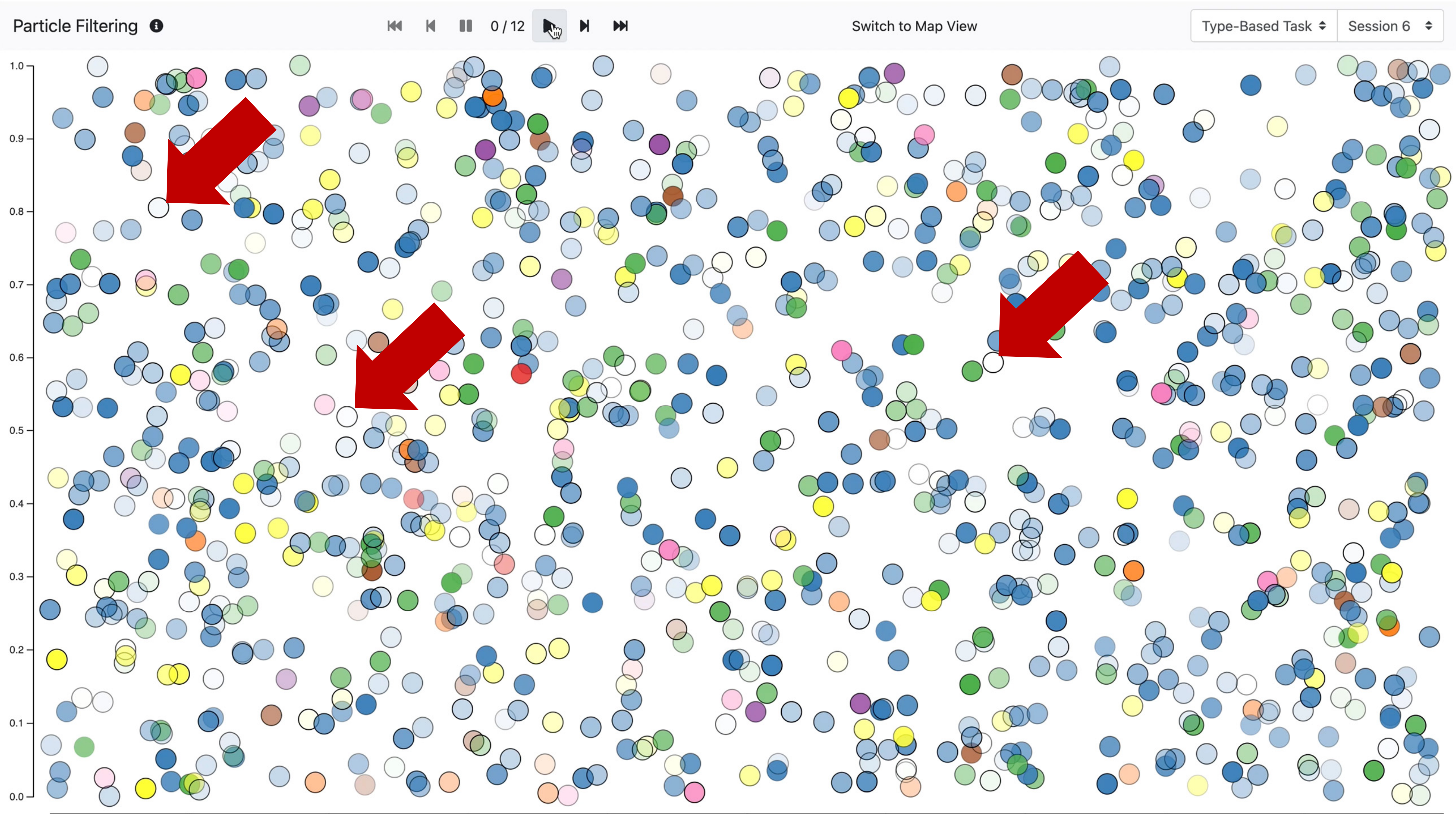
Vagrancy



Particle Filtering
0 / 12
Switch to Map View
Type-Based Task
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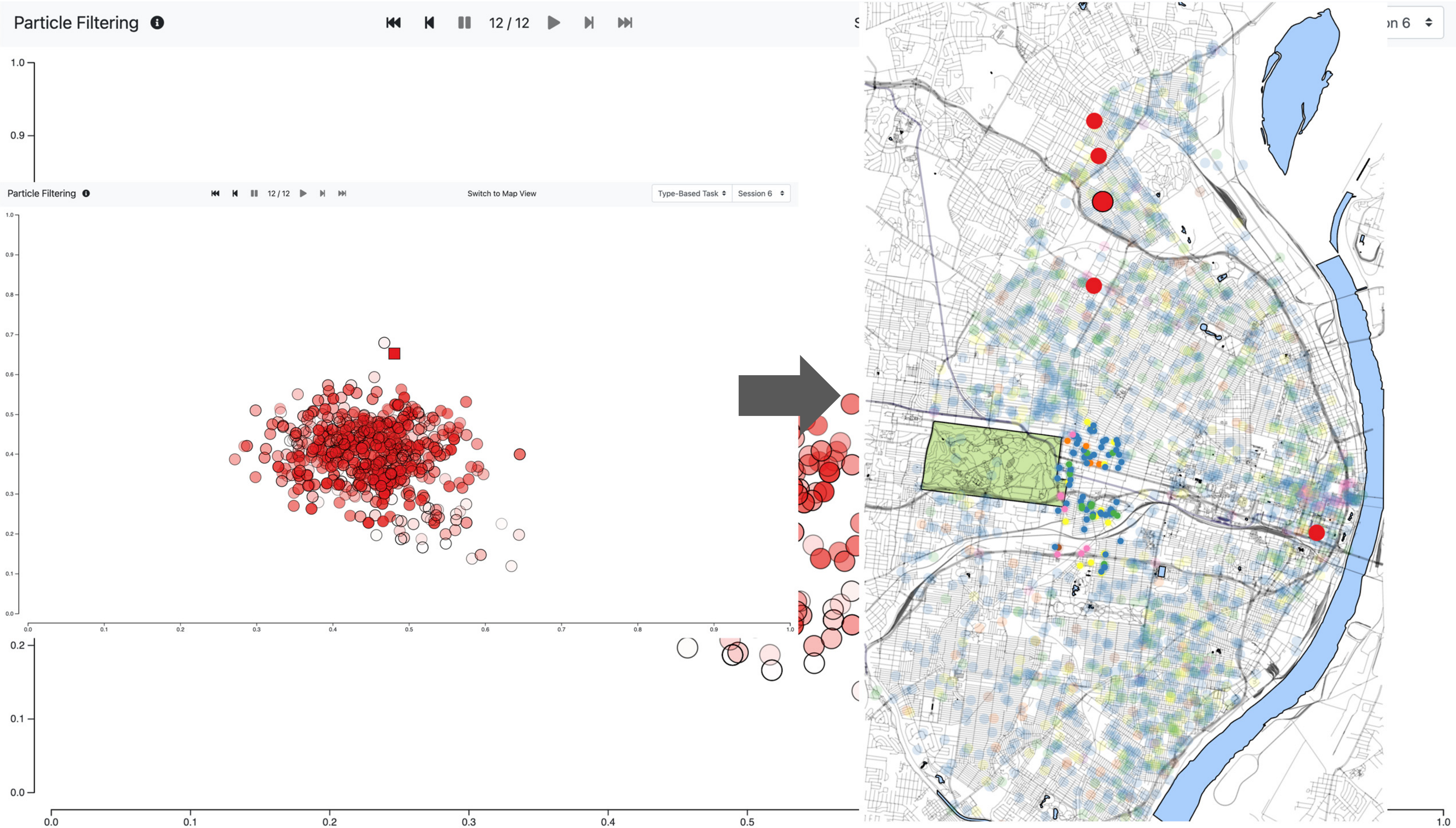
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0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

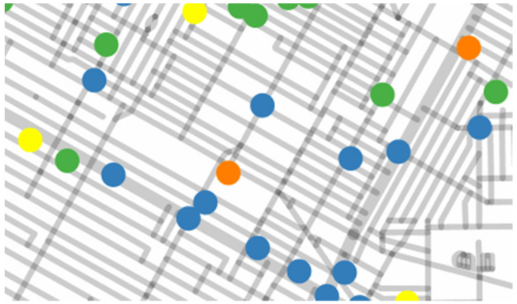
All models are wrong, but some are useful.

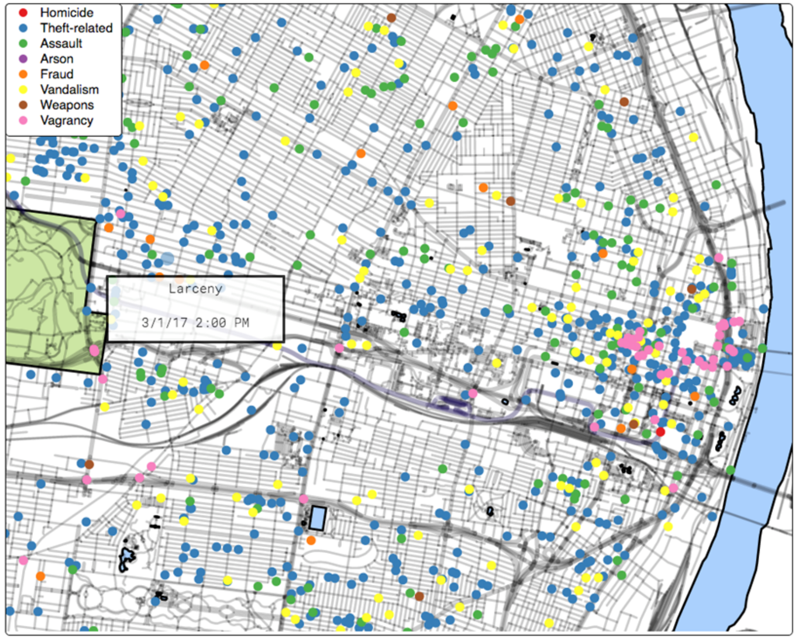
- George E. P. Box

Study Procedures

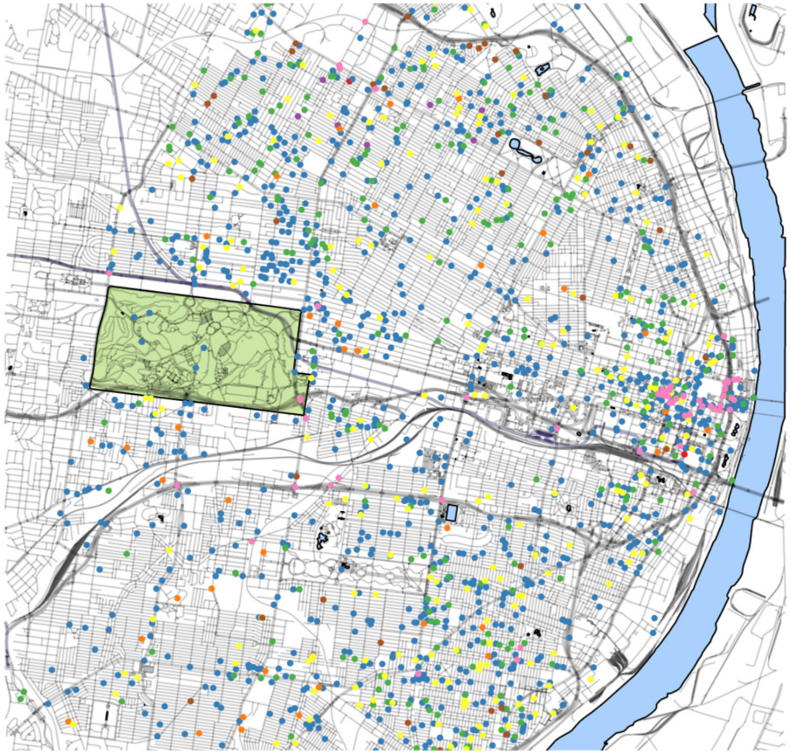
amazon mechanical turk

- 30 subjects
- 17 women
- Average age of 33





Type-Based Task

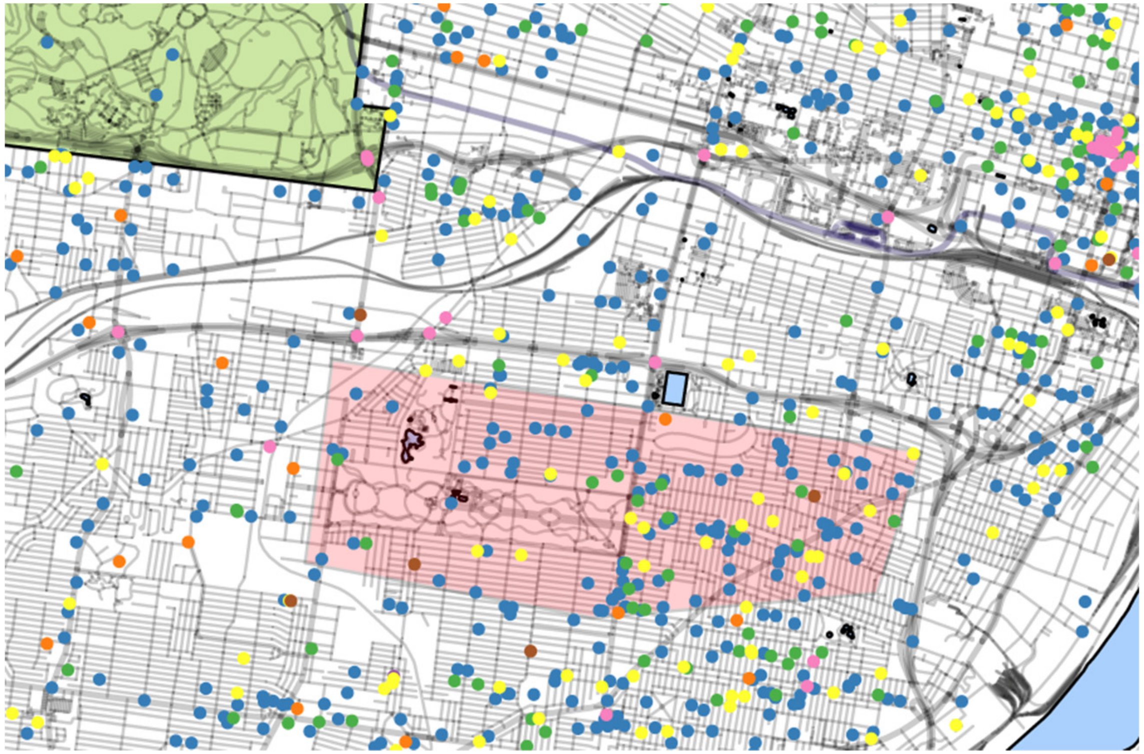


E.g., Find the Homicide that differs from the others.

Geo-Based Task

E.g., In the red-shaded area, what is the ratio of crimes that happened in the morning?

Mixed Type

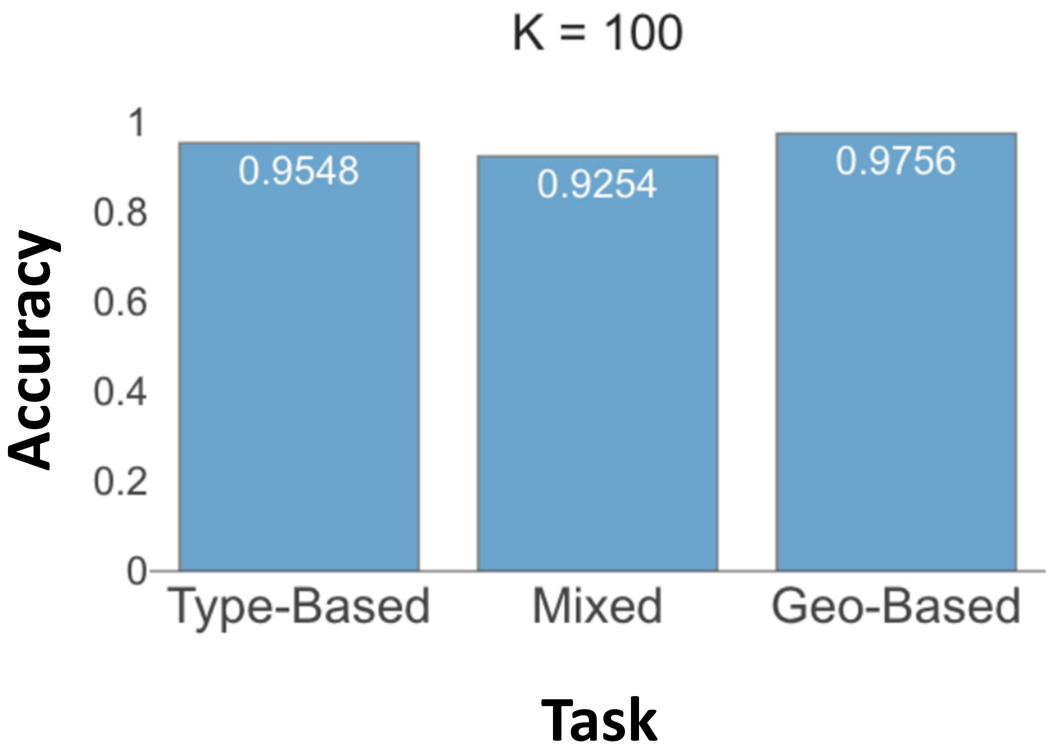


E.g., In the red-shaded area, what is the ratio of theft crimes?

Data Collection & Cleaning

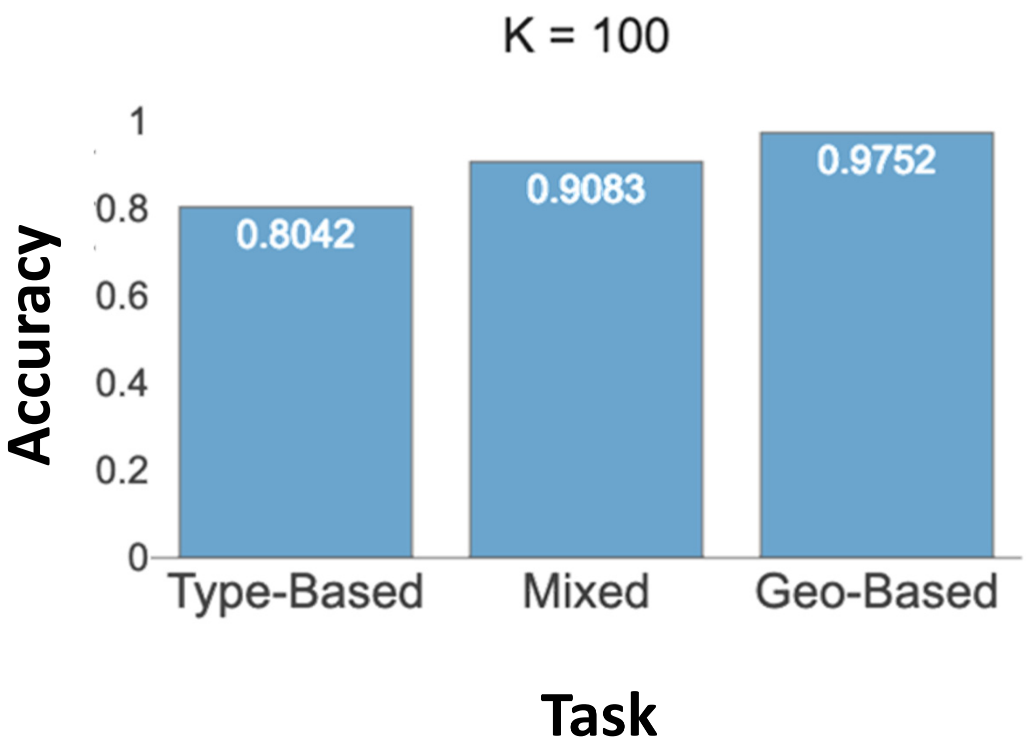
- 30 participants: 180 trials in total
- After cleaning 78 trials remained
  - (23, 27, and 28 trials for Type-Based, Mixed and Geo-Based tasks respectively)

Prediction Accuracy



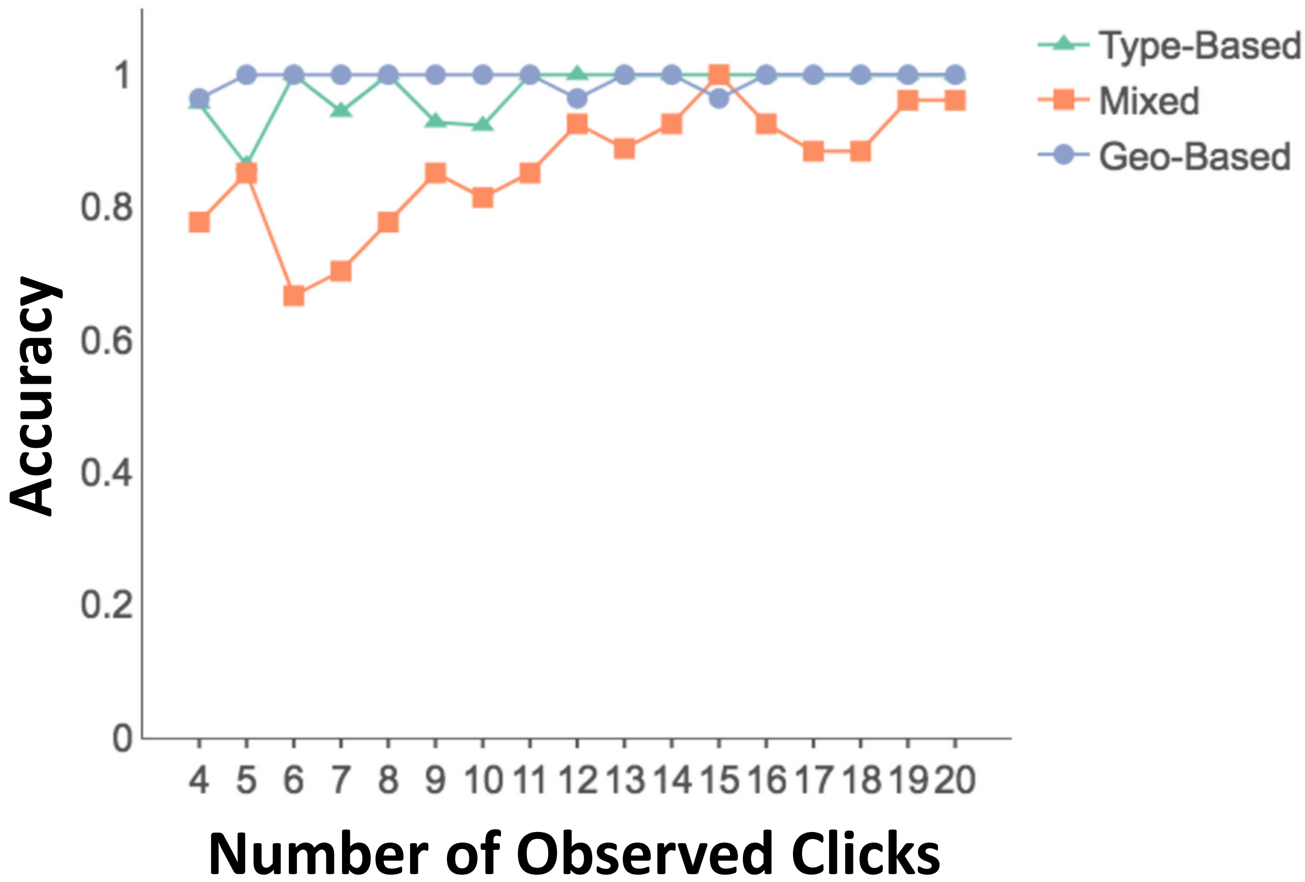
$$\frac{\sum successfulPredictions}{\sum predictions}$$

Prediction Accuracy (with noise)



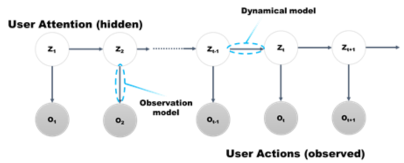
$$\frac{\sum successfulPredictions}{\sum predictions}$$

Accuracy Over Time



Summary

- This a framework for representing, modeling, and predicting latent attention

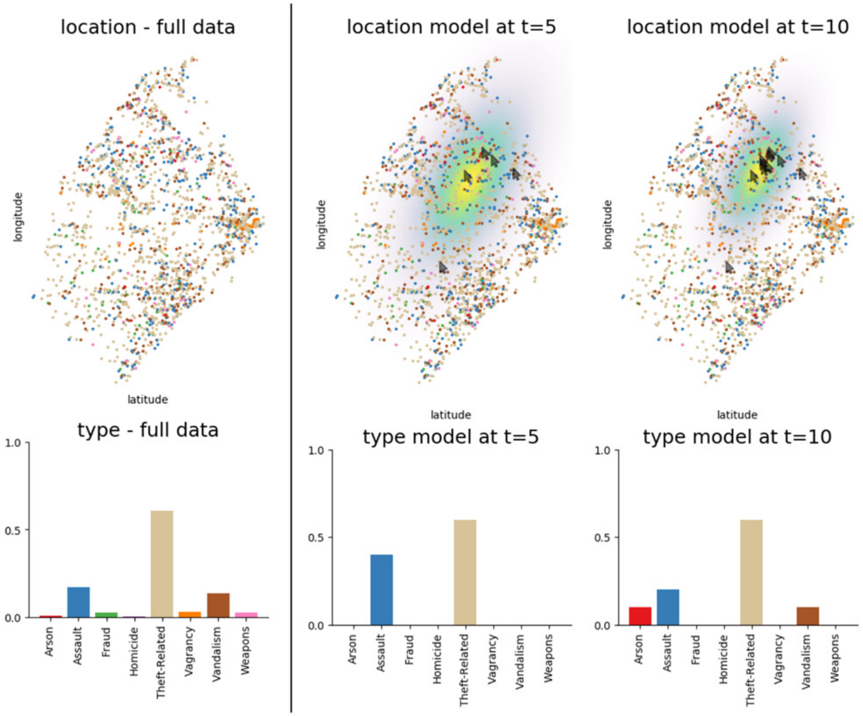


- Demonstrate that the model can accurately predict attention and interactions before they occur.

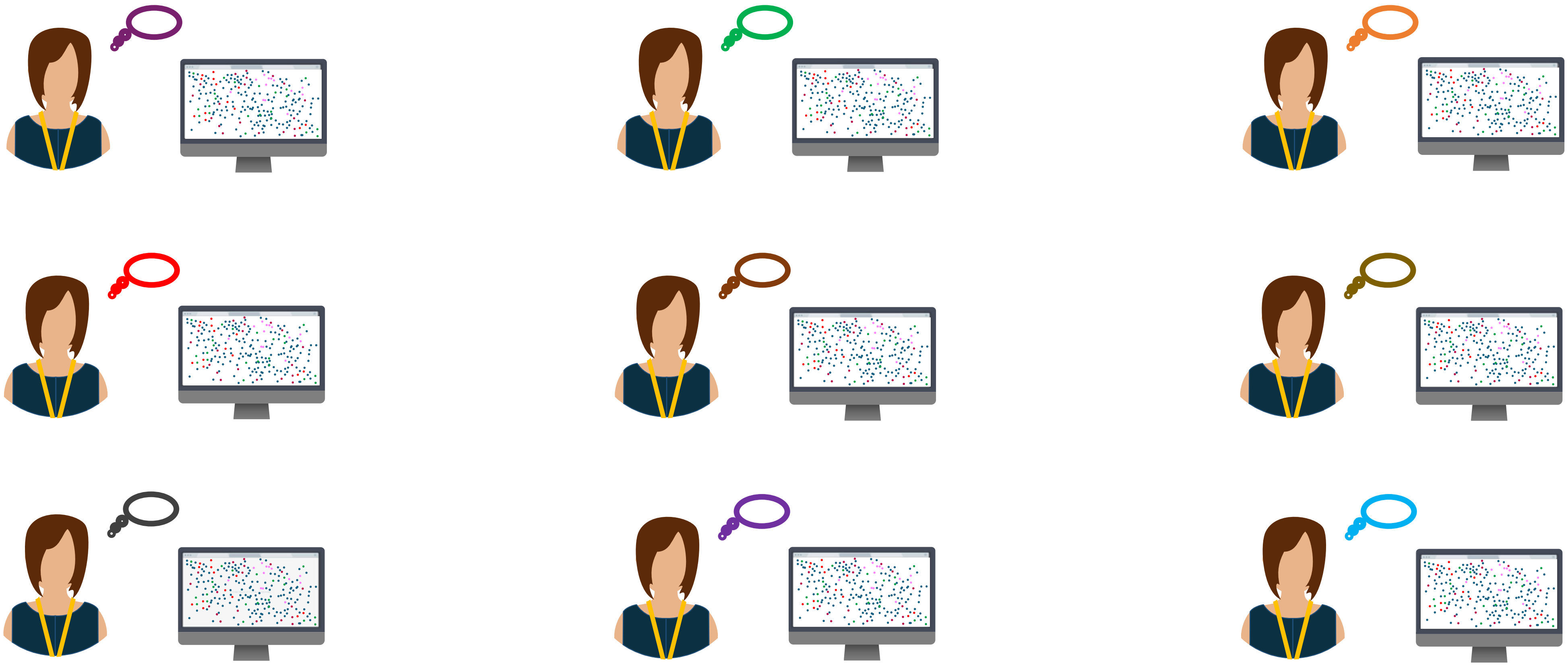
Ottley, Alvitta, Roman Garnett, and Ran Wan. "Follow the clicks: Learning and anticipating mouse interactions during exploratory data analysis." In *Computer Graphics Forum*, vol. 38, no. 3, pp. 41-52. 2019.

Competing Models: Inferring Exploration Patterns and Information Relevance via Bayesian Model Selection

Shayan Monadjemi, Roman Garnett, and Alvitta Ottley



We assume that attributes drive a user's interactions



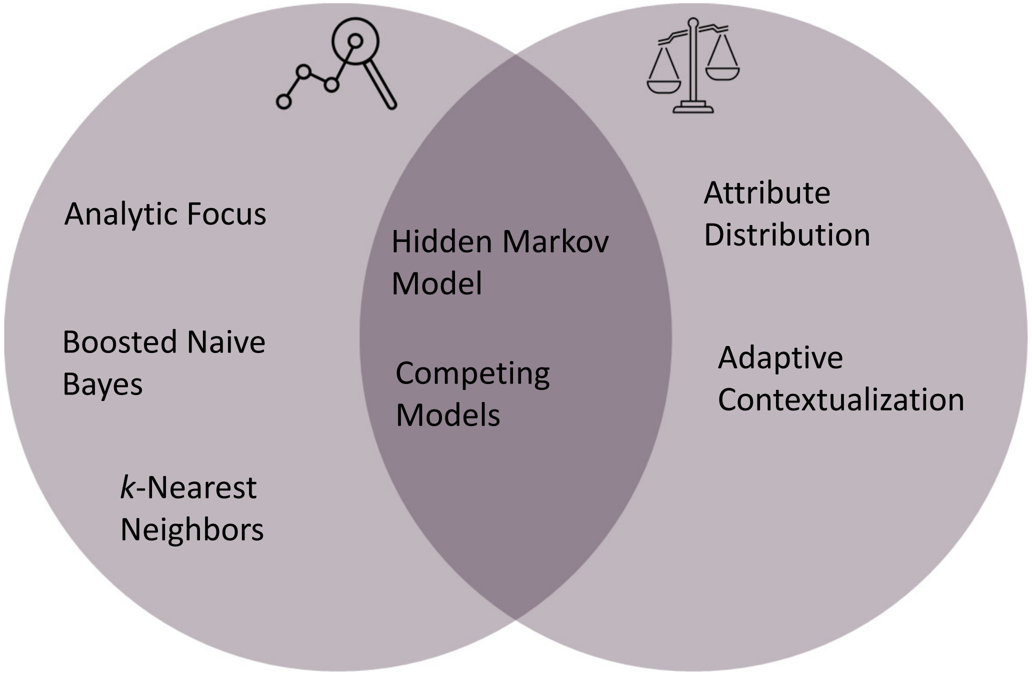
Competing Models

	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$	$\mathcal{M}_5$	$\mathcal{M}_6$	$\mathcal{M}_7$	$\mathcal{M}_8$
Attr 1	×	✓	×	×	✓	×	✓	✓
Attr 2	×	×	✓	×	✓	✓	×	✓
Attr 3	×	×	×	✓	×	✓	✓	✓

$$\underbrace{p(\mathcal{M}_i \mid \text{interactions})}_{\text{Posterior}} \propto \underbrace{p(\text{interactions} \mid \mathcal{M}_i)}_{\text{Likelihood}} \underbrace{p(\mathcal{M}_i)}_{\text{Prior}}$$

A Unified Comparison of User Modeling Techniques for Predicting Data Interaction and Detecting Exploration Bias

Sunwoo Ha, Shayan Monadjemi, Roman Garnett, and Alvitta Ottley



Challenge 2
Create a feedback loop. How might we respond to learned behavior and manage the communication from AI to user?

Guided Data Discovery in Interactive Visualizations via Active Search

Shayan Monadjemi*
Washington University in St. Louis

Sunwoo Ha†
Washington University in St. Louis

Quan Nguyen
Washington University in St. Louis

Henry Chai
Carnegie Mellon University

Roman Garnett
Washington University in St. Louis

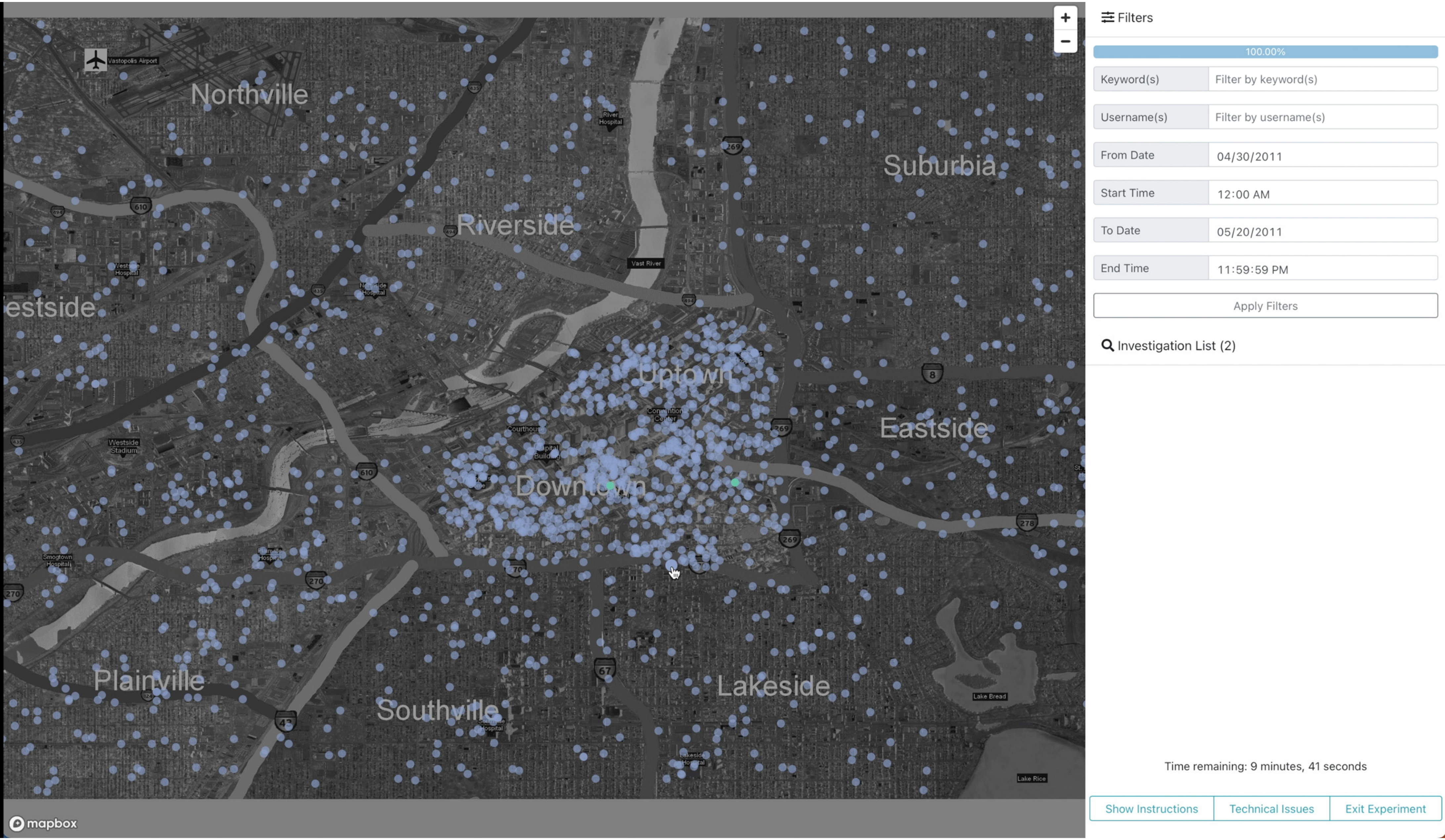
Alvitta Ottley‡
Washington University in St. Louis

Providing guidance during data exploration

We aimed to:

- Create a human–machine team for interactive data discovery.
- Empirically evaluate the impact of such team on user interactions and discovery throughput.

Monadjemi, Shayan, Sunwoo Ha, Quan Nguyen, Henry Chai, Roman Garnett, and Alvitta Ottley. "Guided Data Discovery in Interactive Visualizations via Active Search." In 2022 IEEE Visualization and Visual Analytics (VIS), pp. 70-74. IEEE, 2022.


Vastopolis Airport
Northville
Suburbia
Riverside
River Hospital
Vast River
estside
Westside Hospital
Uptown
Convention Center
Courthouse
Eastside
Westside Stadium
Downtown
Plainville
Southville
Lakeside
Lake Bread
Lake Rice
mapbox
Filters
100.00%
Keyword(s)
Filter by keyword(s)
Username(s)
Filter by username(s)
From Date
04/30/2011
Start Time
12:00 AM
To Date
05/20/2011
End Time
11:59:59 PM
Apply Filters
Investigation List (2)
Time remaining: 9 minutes, 41 seconds
Show Instructions
Technical Issues
Exit Experiment

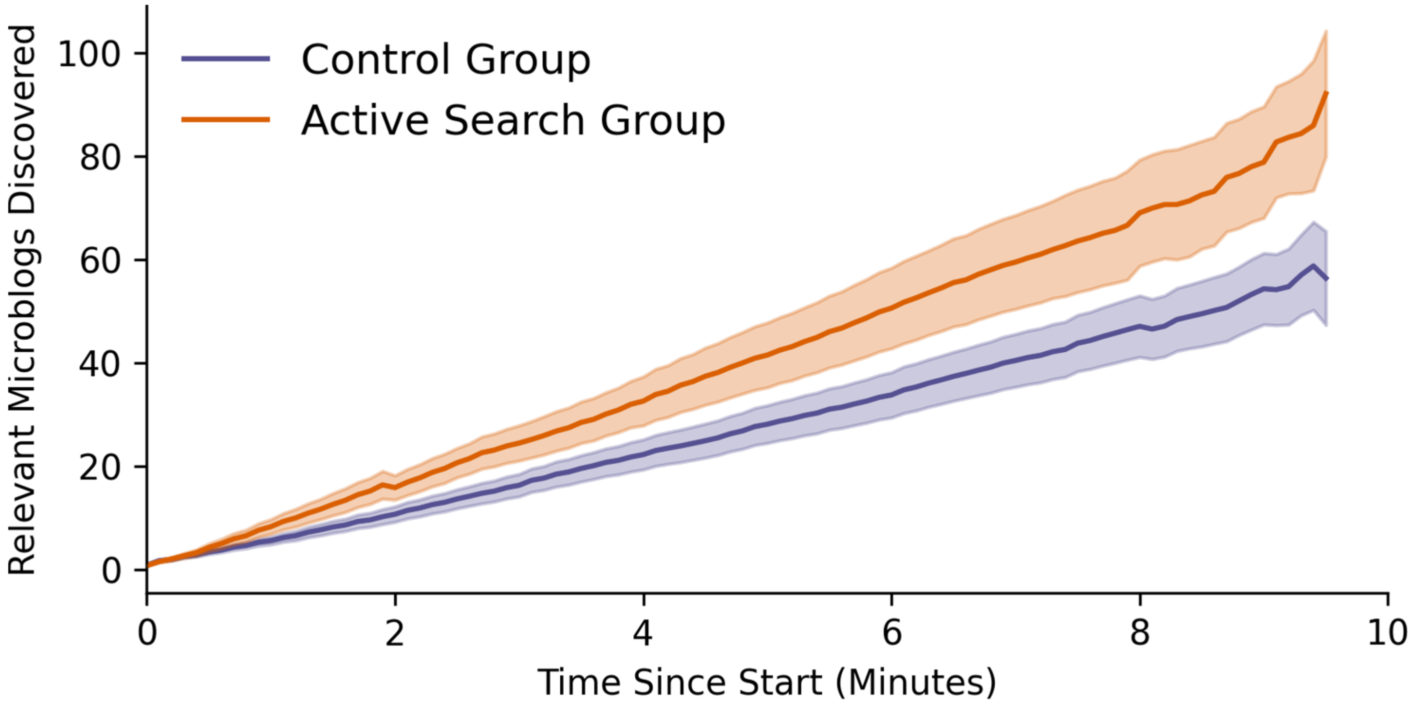
Crowd-sourced User Study

Control Group

Active Search Group

10 Minutes

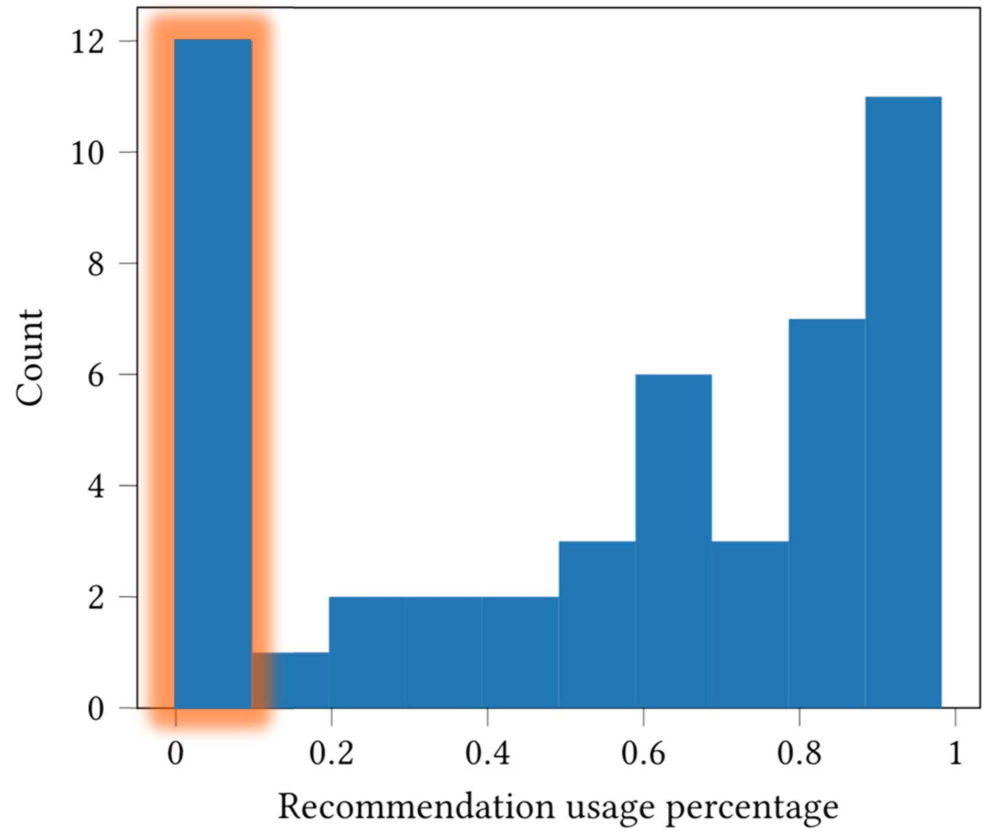
Crowd-sourced User Study



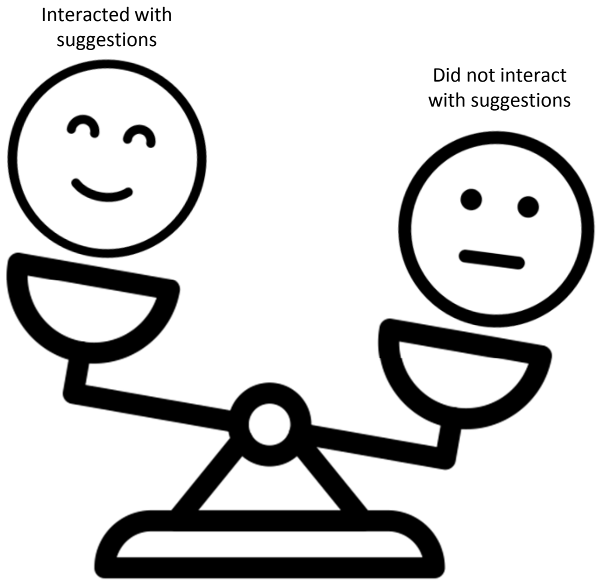
Crowd-sourced User Study

	Control Group	Active Search Group	
Hovers per Minute	$\boxed{16.7 \pm 1.19}$	14.3 ± 1.23	$p = 0.0112$
Relevant Hovers per Minute	6.7 ± 0.68	9.2 ± 1.12	$p = 0.0001$
Hover Purity	0.39 ± 0.02	0.63 ± 0.05	$p < 0.0001$

A large percentage of people ignored the recommendations



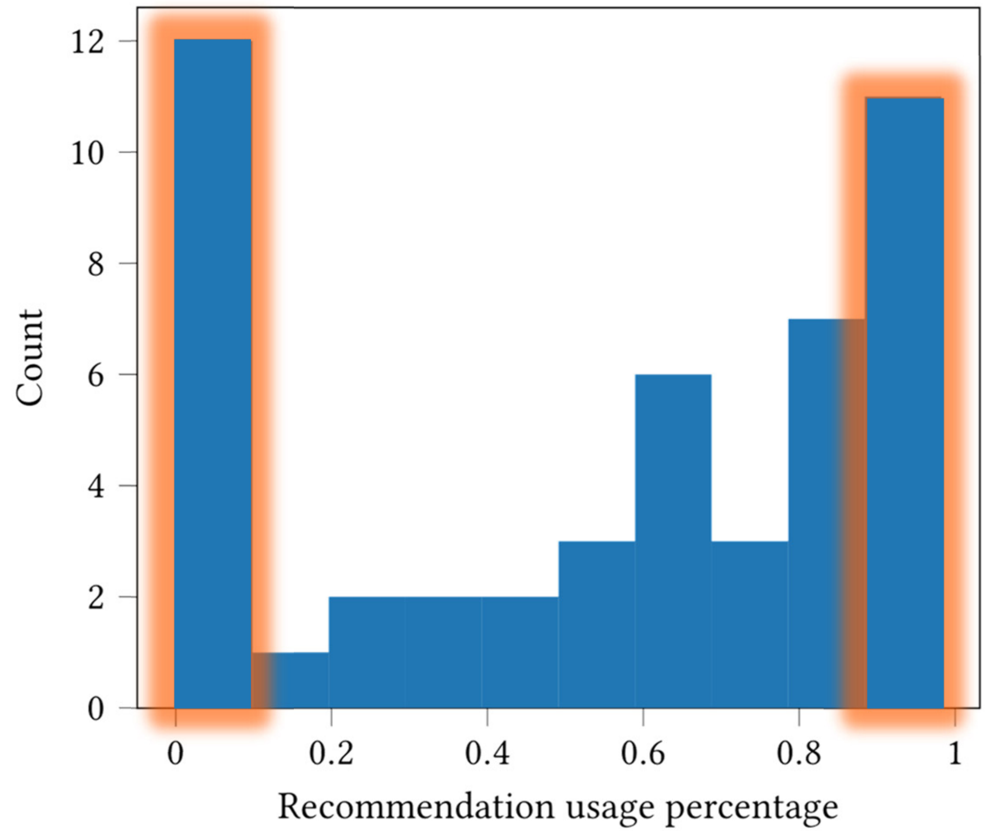
Those who didn’t use recommendations were most likely to see they didn’t ***trust*** the suggestions.



Monadjemi, Shayan, Sunwoo Ha, Quan Nguyen, Henry Chai, Roman Garnett, and Alvitta Ottley. "Guided Data Discovery in Interactive Visualizations via Active Search." In 2022 IEEE Visualization and Visual Analytics (VIS), pp. 70-74. IEEE, 2022.

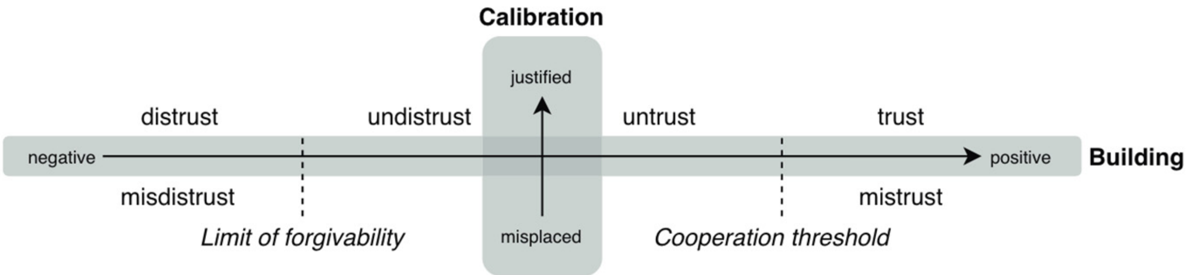
A large percentage of people ignored the recommendations

Blind trust can be equally problematic



Trust Calibration

- There are several levels of trust: distrust, trust, blind trust
- Trust calibration aligns the trust put into a VA system by the user with the machine's actual trustworthiness through communicating uncertainties, providing visual cues, etc.

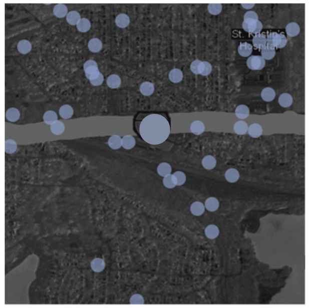


Han, Wenkai, and Hans-Jörg Schulz. "Beyond trust building—Calibrating trust in visual analytics." In 2020 IEEE workshop on trust and expertise in visual analytics (TREX), pp. 9-15. IEEE, 2020.

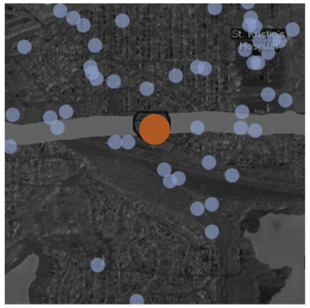
Zhang, Yunfeng, Q. Vera Liao, and Rachel KE Bellamy. "Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making." In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, pp. 295-305. 2020.

TRUST

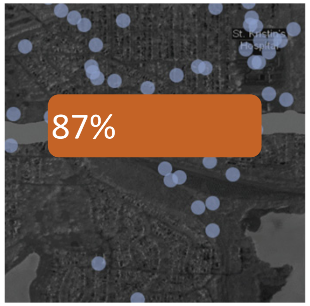
Trust calibration, controlling for transparency level and task difficulty



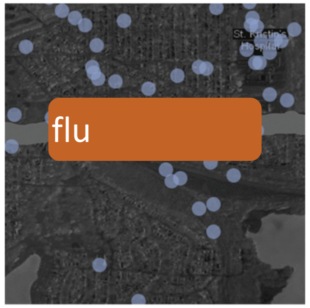
Control



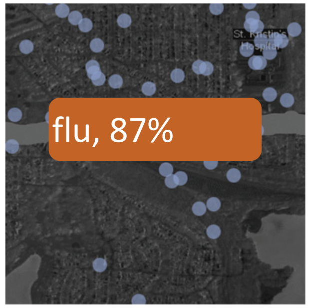
No Explanations



Confidence

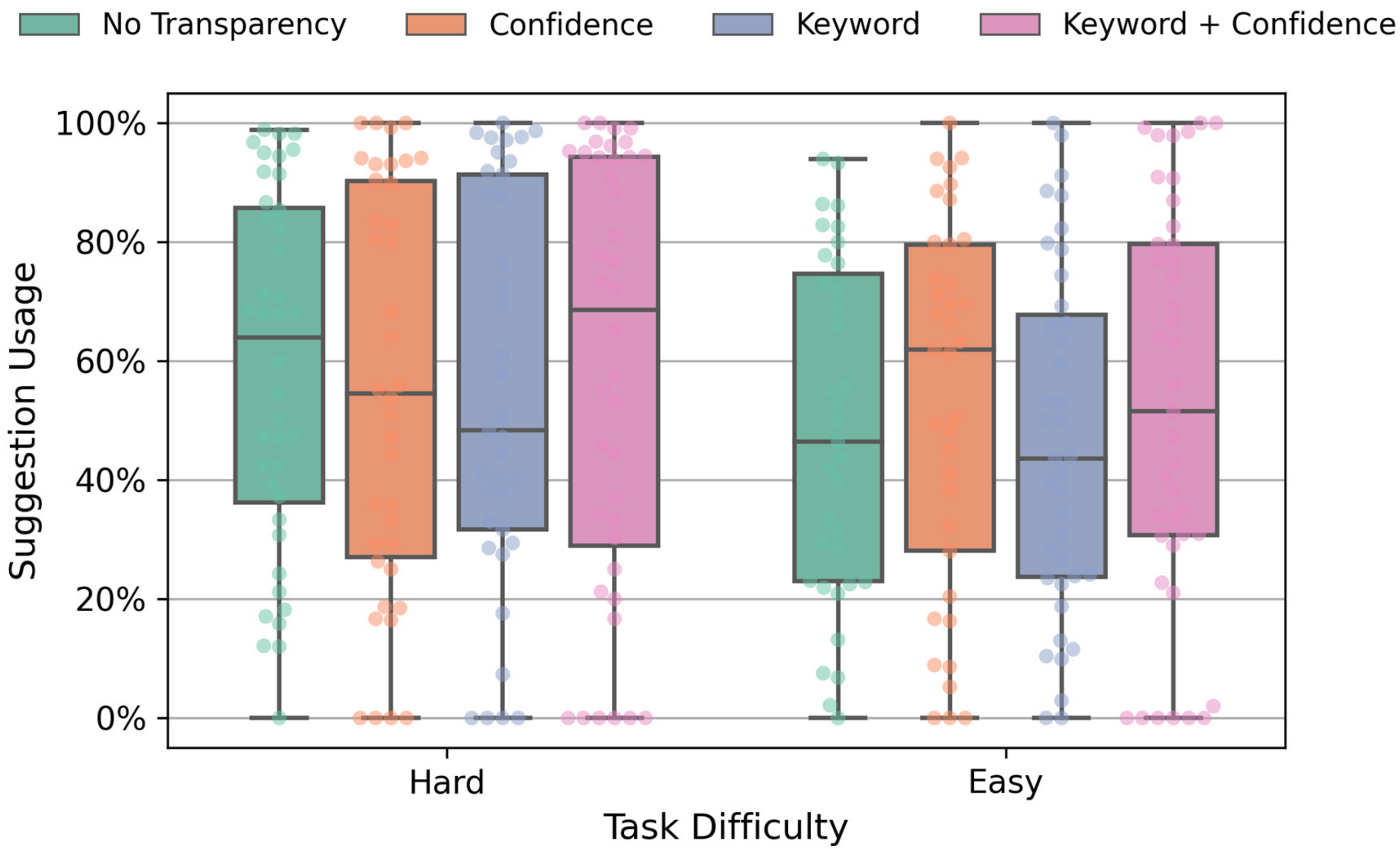


Keyword

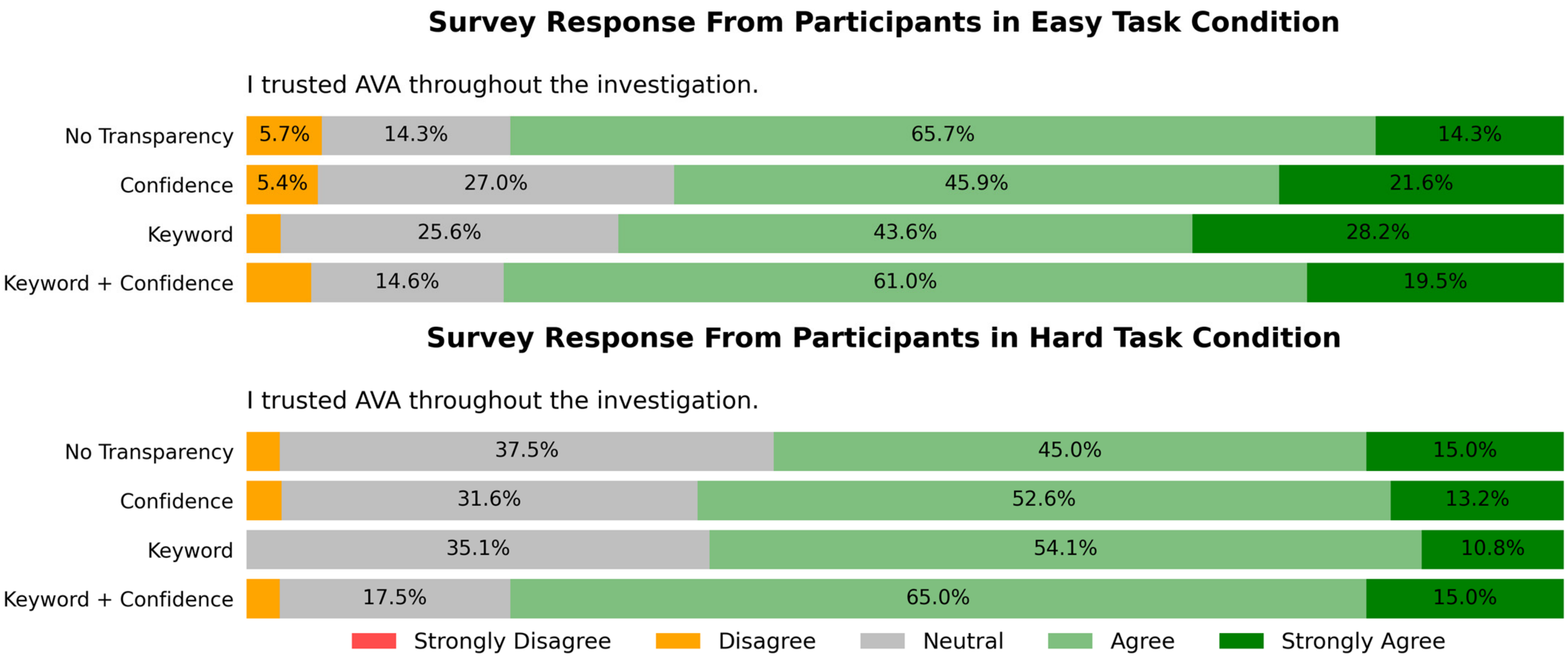


Keyword + Confidence

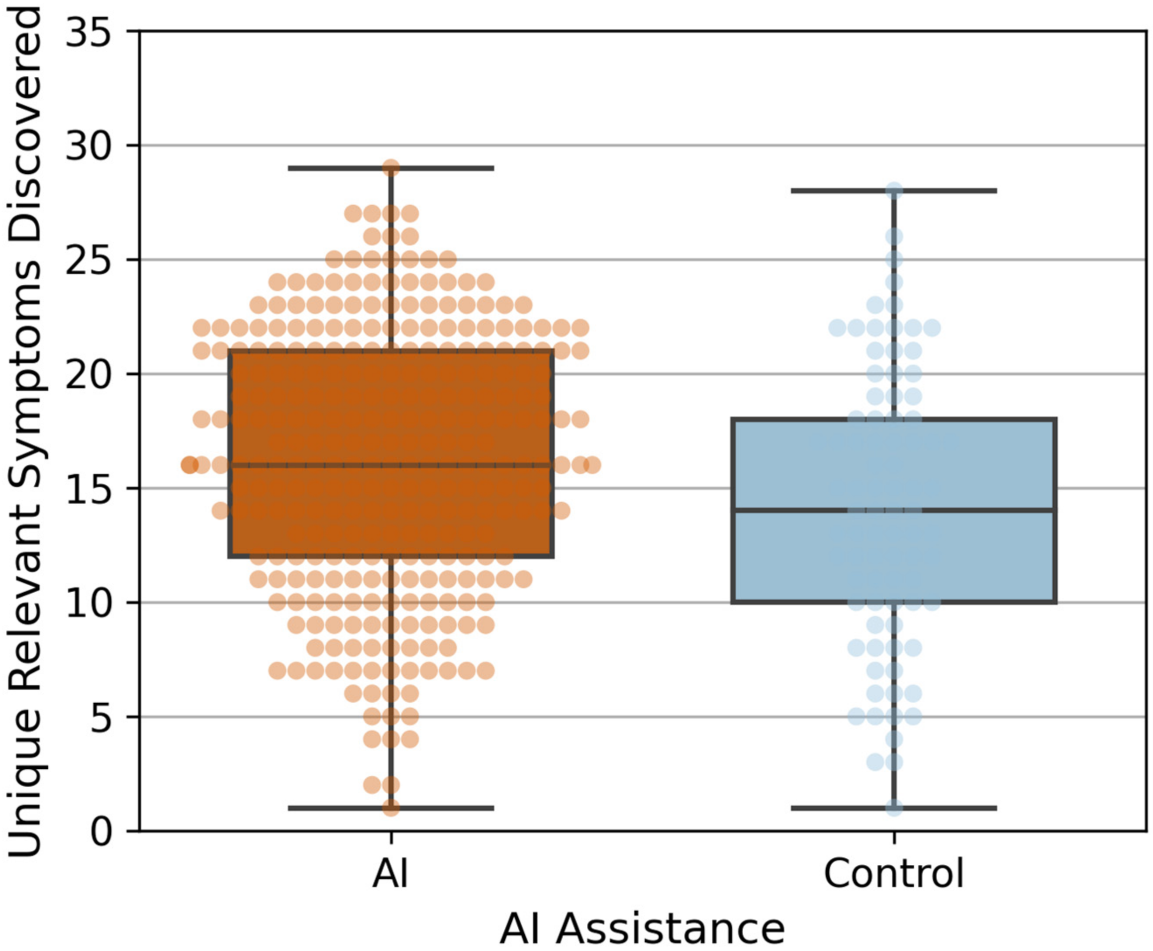
No measurable difference in behavioral trust



No measurable difference in subjective trust



AI guidance encouraged exploration diversity



Challenge 3
Develop new theoretical models that acknowledge the collaborative potential of AI. What are the ramifications?

Human—Computer Collaboration for Visual Analytics: an Agent-based Framework

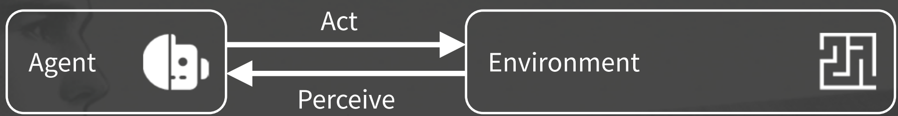
Shayan Monadjemi[1], Mengtian Guo[2], David Gotz[2], Roman Garnett[1], Alvitta Ottley[1]

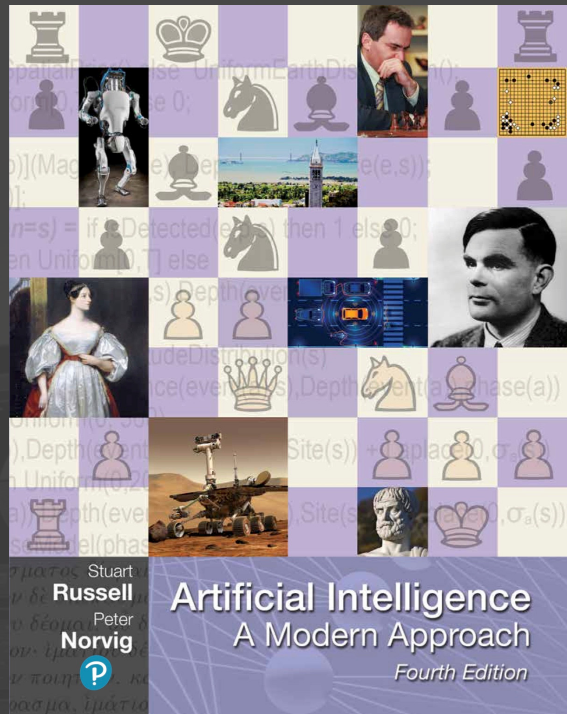
[1] Washington University in St. Louis

[2] University of North Carolina at Chapel Hill


I can make decisions and initiate actions.

I can make decisions and initiate actions.



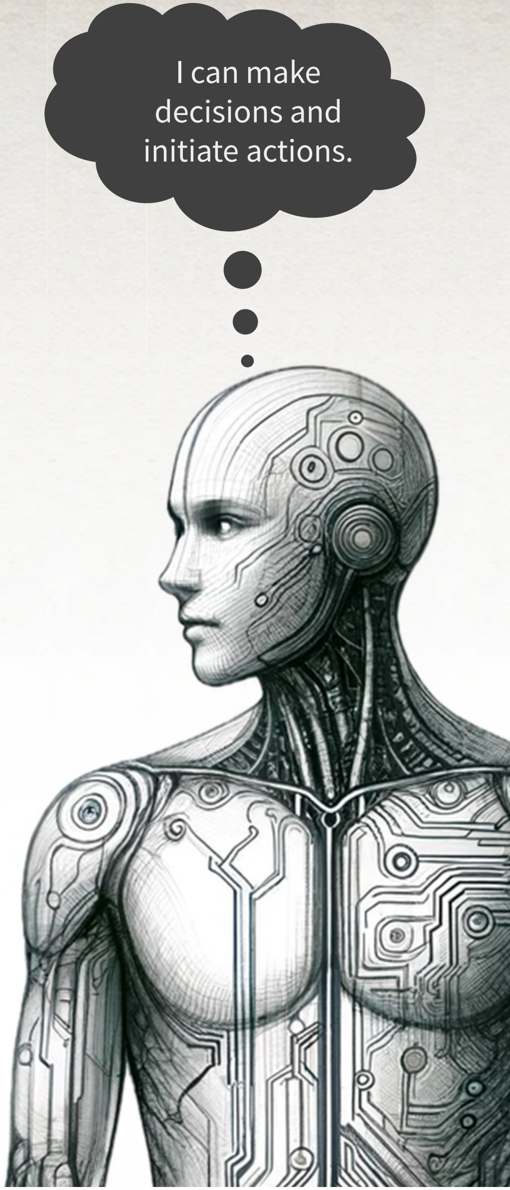


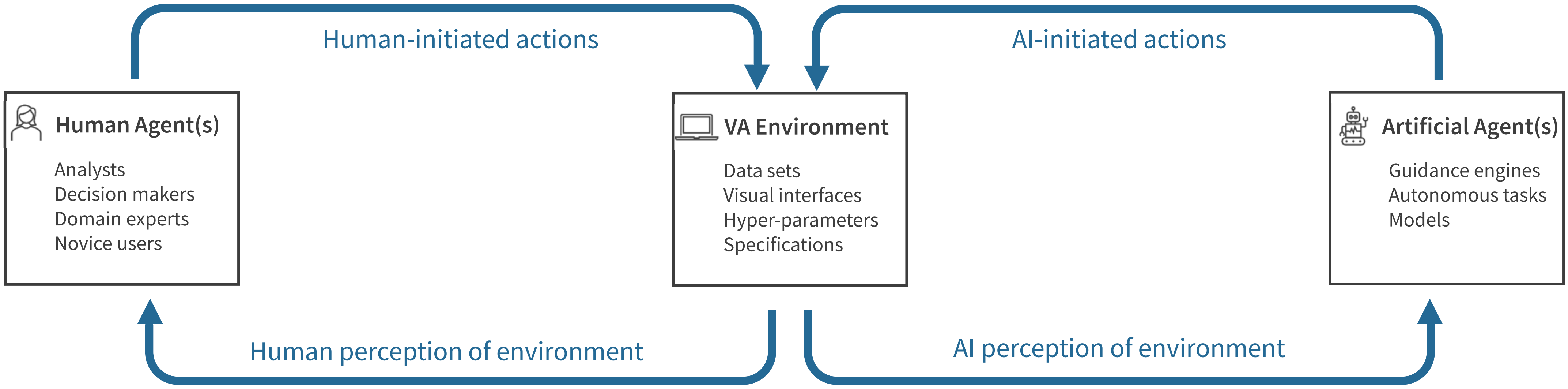
The AI agent framework gives us a vocabulary to reason about the analyst’s goals and behavior

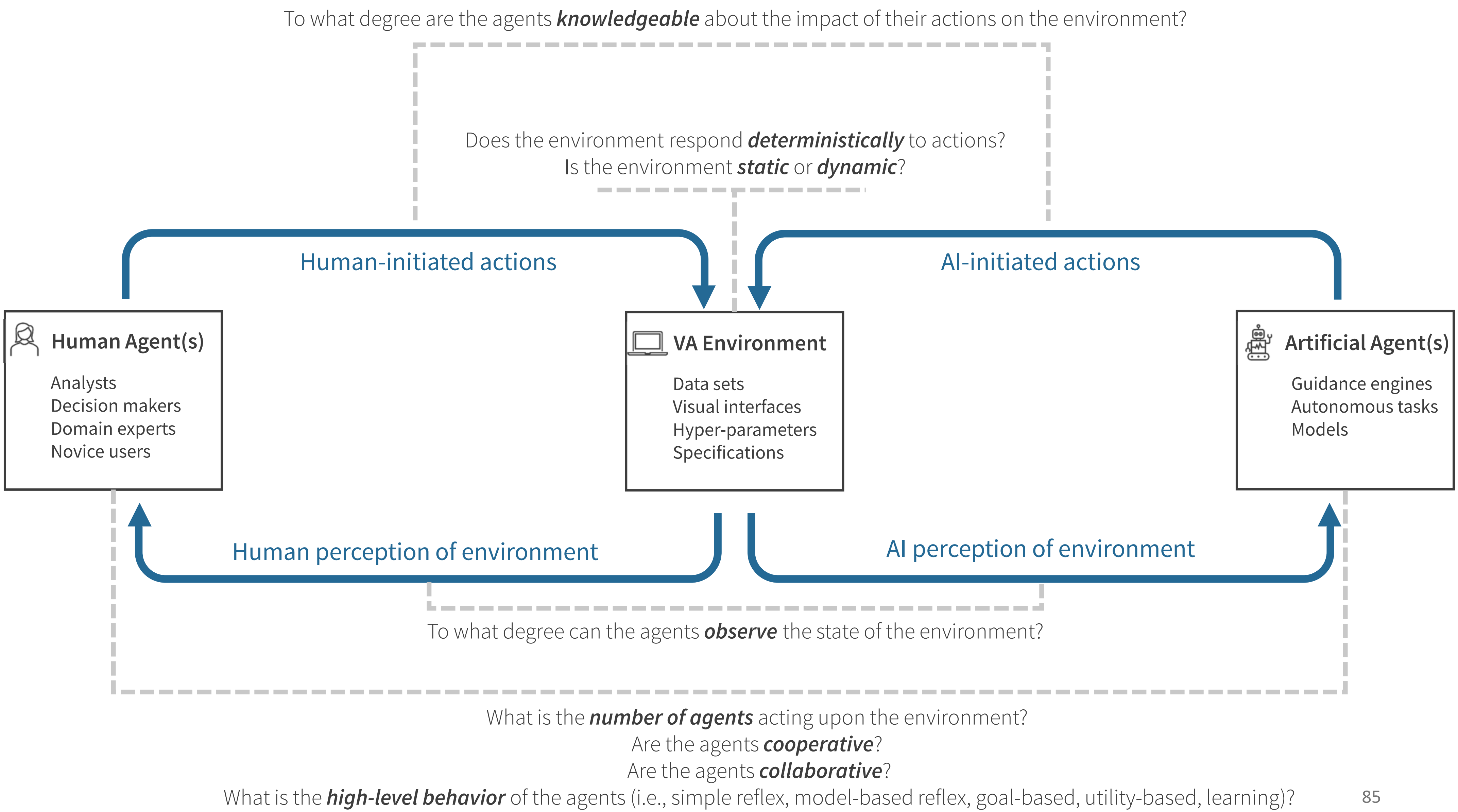
- Simple Reflex
- Model-Based
- Goal-Based
- Utility-Based
- Learning

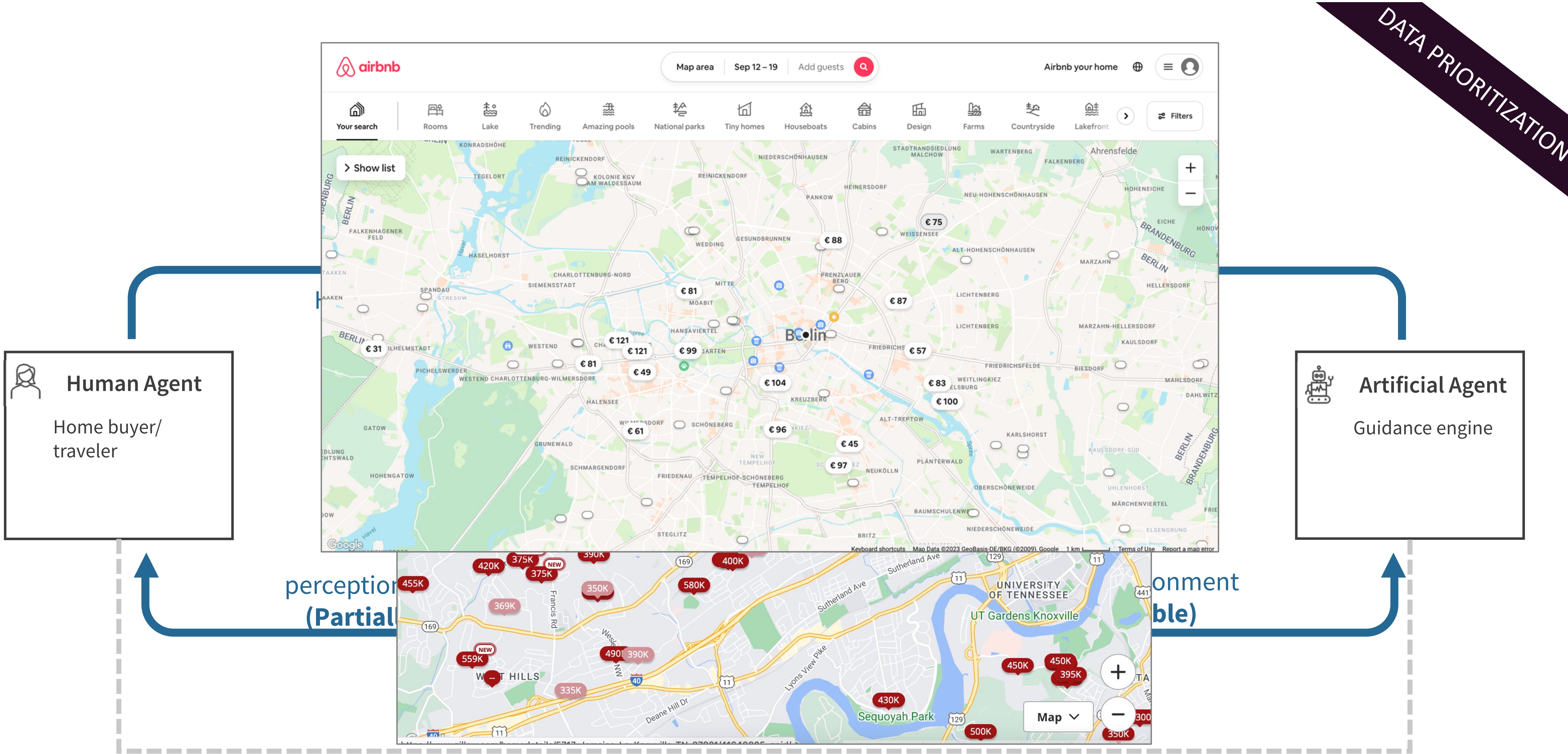
The AI agent framework gives us a vocabulary to reason about the analyst’s goals and behavior

- Simple Reflex
- Model-Based
- Goal-Based
- Utility-Based
- Learning

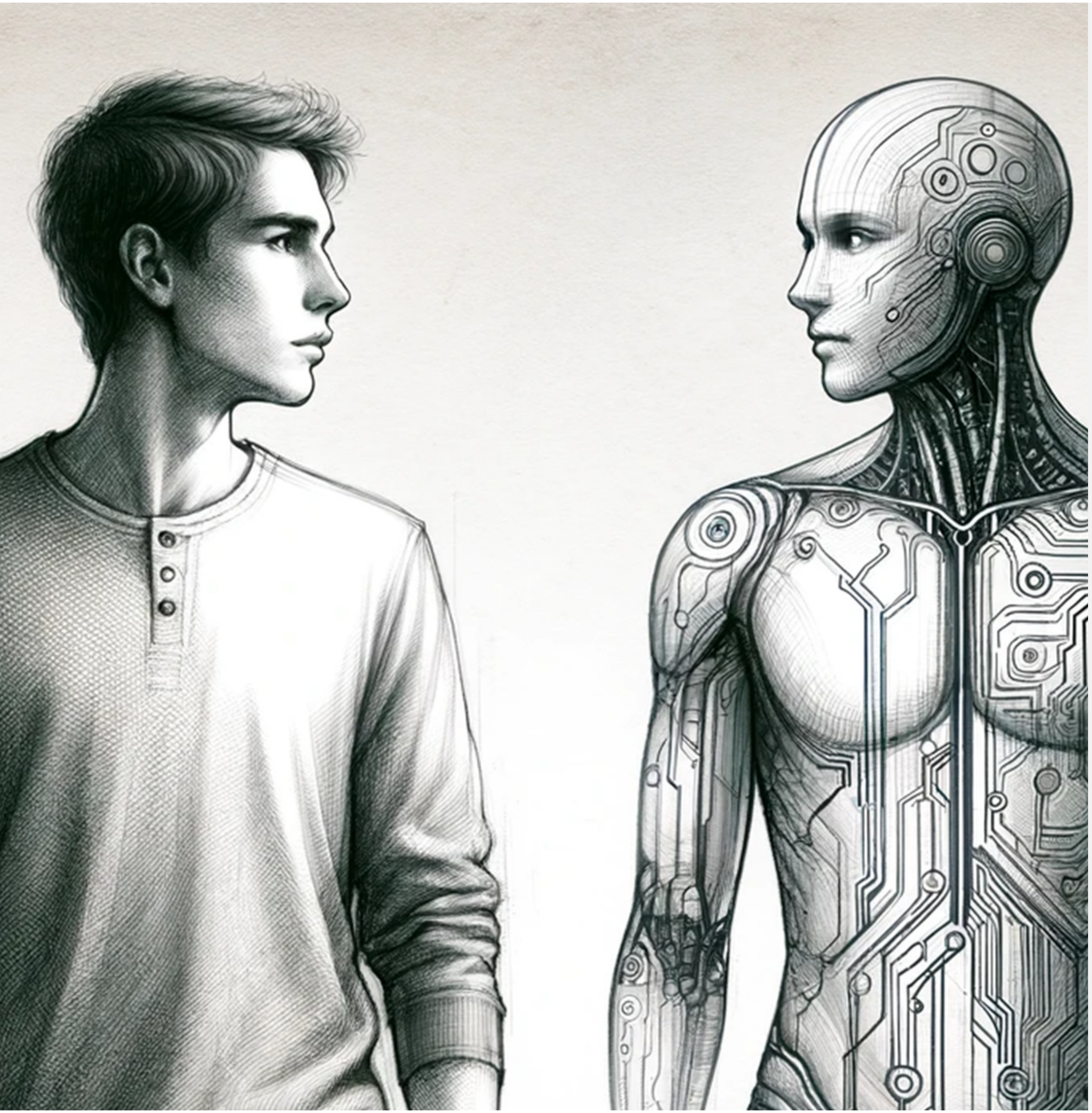



Human-initiated actions
AI-initiated actions
Human Agent(s)
Analysts
Decision makers
Domain experts
Novice users
VA Environment
Data sets
Visual interfaces
Hyper-parameters
Specifications
Artificial Agent(s)
Guidance engines
Autonomous tasks
Models
Human perception of environment
AI perception of environment


To what degree are the agents ***knowledgeable*** about the impact of their actions on the environment?
Does the environment respond ***deterministically*** to actions?
Is the environment ***static*** or ***dynamic***?
Human-initiated actions
AI-initiated actions
Human Agent(s)
Analysts
Decision makers
Domain experts
Novice users
VA Environment
Data sets
Visual interfaces
Hyper-parameters
Specifications
Artificial Agent(s)
Guidance engines
Autonomous tasks
Models
Human perception of environment
AI perception of environment
To what degree can the agents ***observe*** the state of the environment?
What is the ***number of agents*** acting upon the environment?
Are the agents ***cooperative***?
Are the agents ***collaborative***?
What is the ***high-level behavior*** of the agents (i.e., simple reflex, model-based reflex, goal-based, utility-based, learning)?



Cooperative? Collaborative? Adversarial?



Is it possible for an AI to collaborate in visual analytics, understanding and predicting our behaviors to enhance our analytical capabilities?

Quietly observe and learn from our actions

Provide guidance based on learning data interest.

One potential theoretical model that acknowledge the collaborative potential of AI.

Acknowledgments

The Predictable Side of Unpredictable Humans

Questions?

Alvitta Ottley

VI BE Visualization Interaction and Behavior Exploration

http://visualdata.wustl.edu/