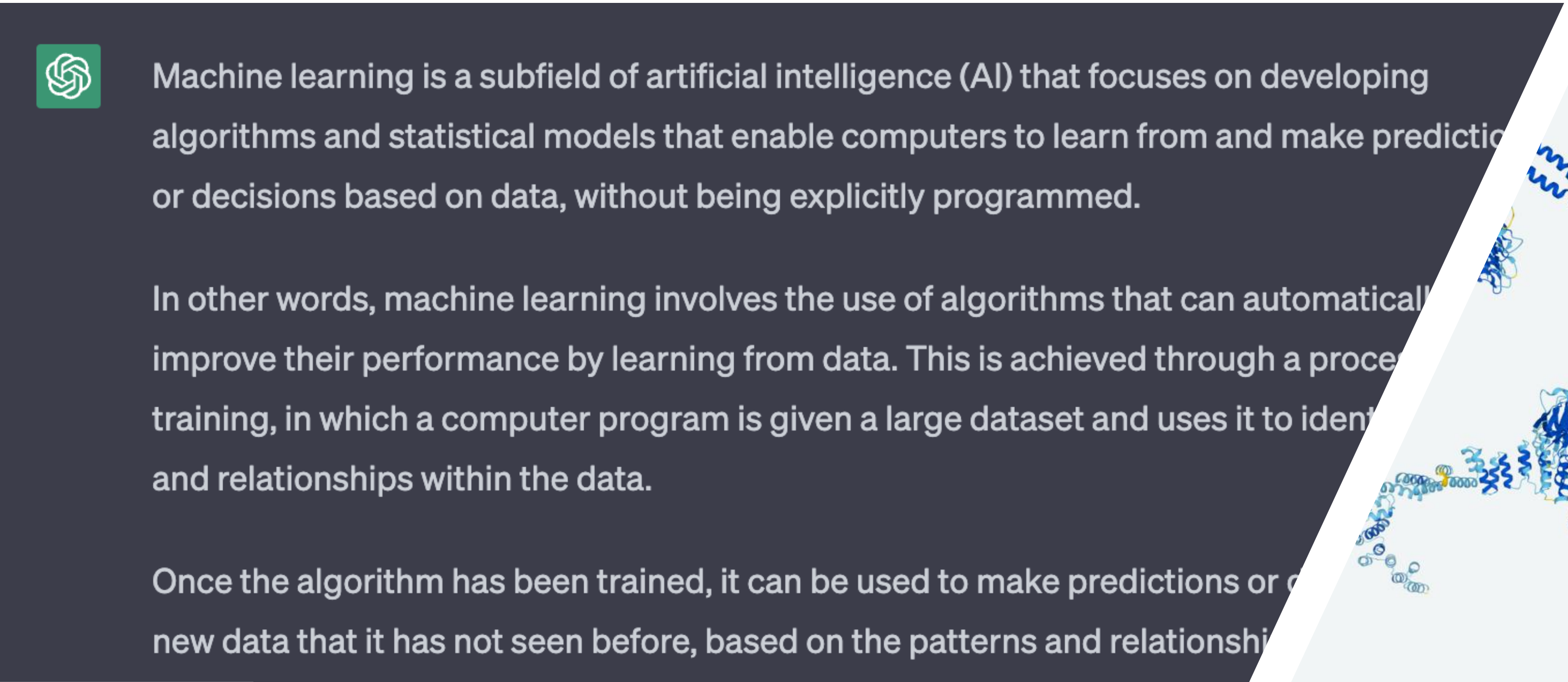
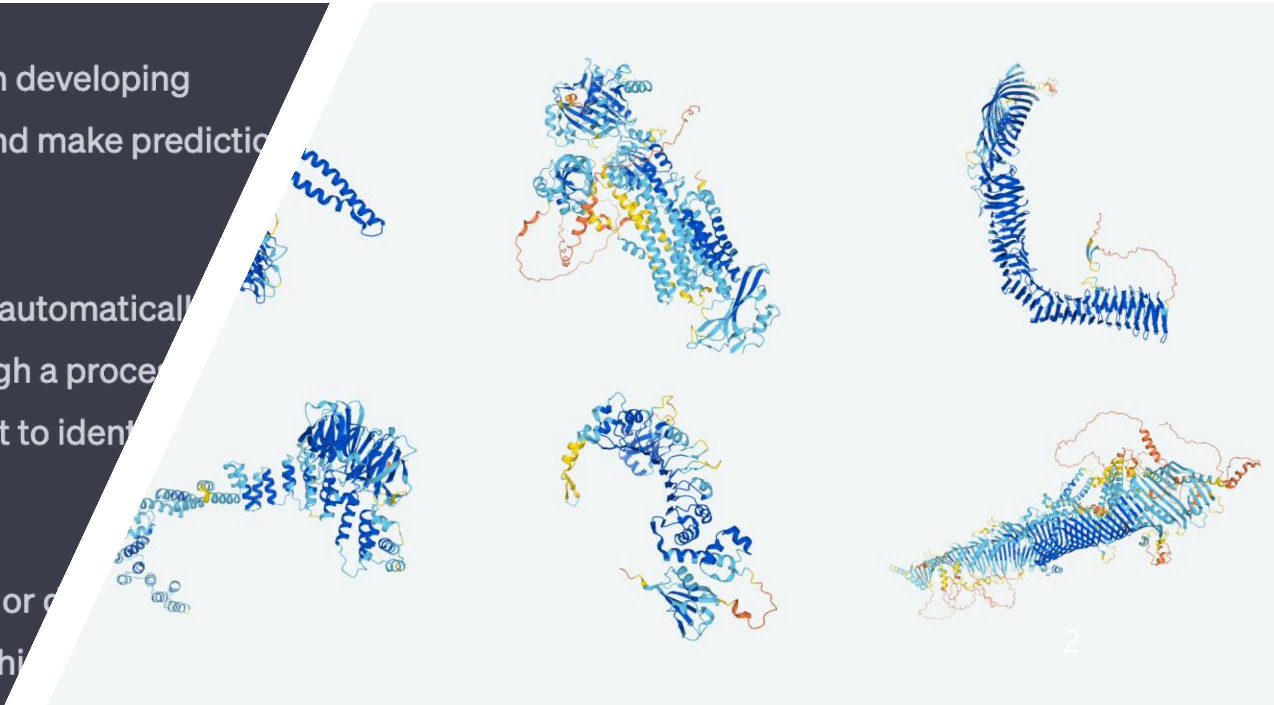
From Data to Dialog: **Visualization-empowered Human-AI Collaboration**

Xinhuan Shu (https://shuxinhuan.github.io)

Lecturer @ Newcastle University

Data Visualization 📊 / Human-Computer Interaction 🖥 / Data-driven Storytelling 🖊


Machine learning is a subfield of artificial intelligence (AI) that focuses on developing algorithms and statistical models that enable computers to learn from and make predictio
or decisions based on data, without being explicitly programmed.
In other words, machine learning involves the use of algorithms that can automaticall
improve their performance by learning from data. This is achieved through a proce
training, in which a computer program is given a large dataset and uses it to ident
and relationships within the data.
Once the algorithm has been trained, it can be used to make predictions or d
new data that it has not seen before, based on the patterns and relationshi

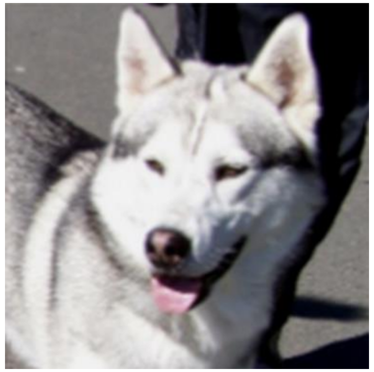


How does AI work?

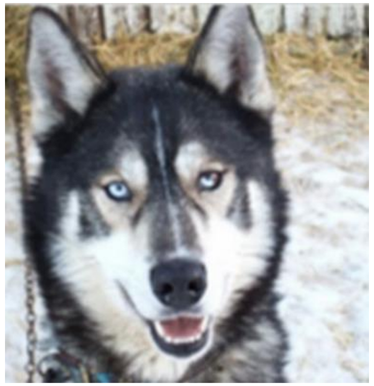
Input

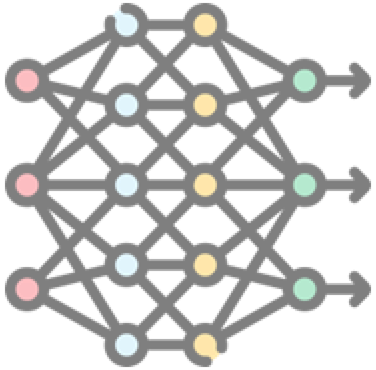
Model

Output



Predicted:
husky ✓





Predicted:
wolf ✗

The New York Times

Opinion

OP-ED CONTRIBUTOR

How to Make A.I. That's Good for People

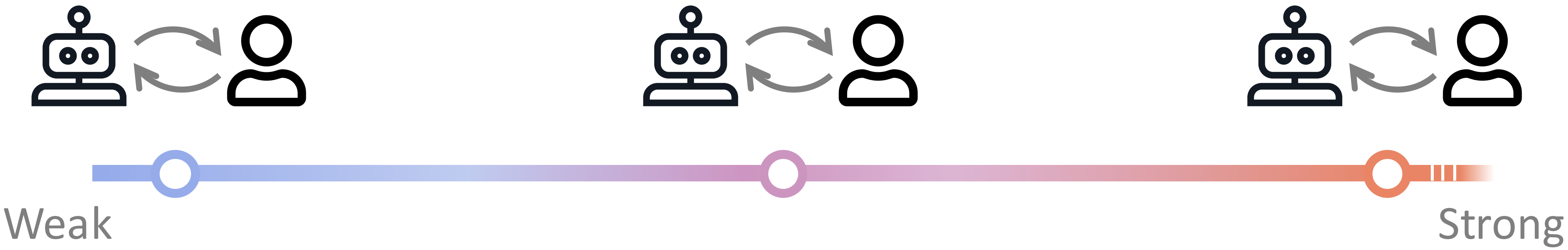
By Fei-Fei Li
March 7, 2018

Give this article

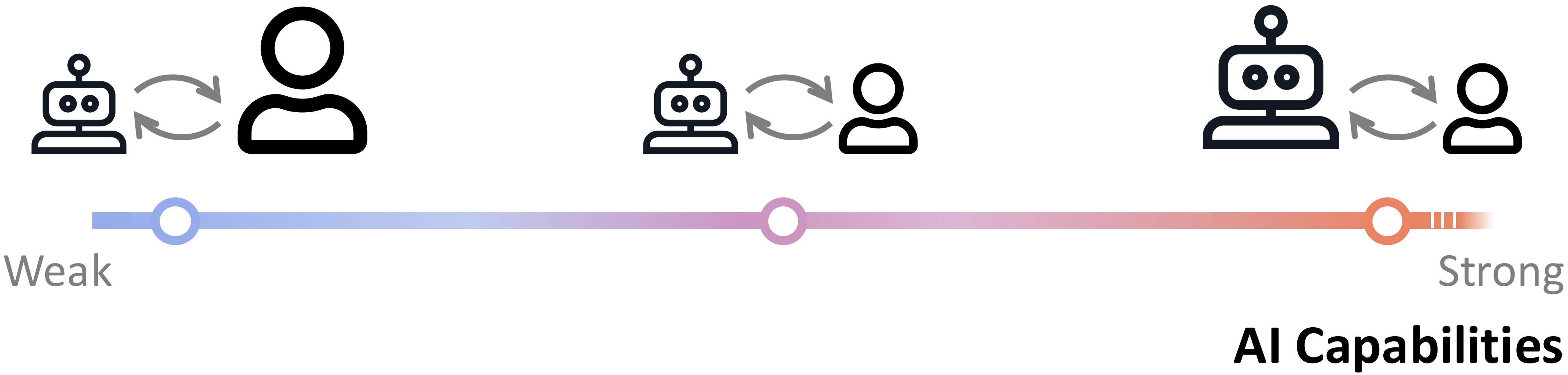
Elisa Macellari

I worry, however, that enthusiasm for A.I. is preventing us from reckoning with its looming effects on society. Despite its name, there is nothing "artificial" about this technology — it is made by humans, intended to behave like humans and affects humans. So **if we want it to play a positive role in tomorrow's world, it must be guided by human concerns.**

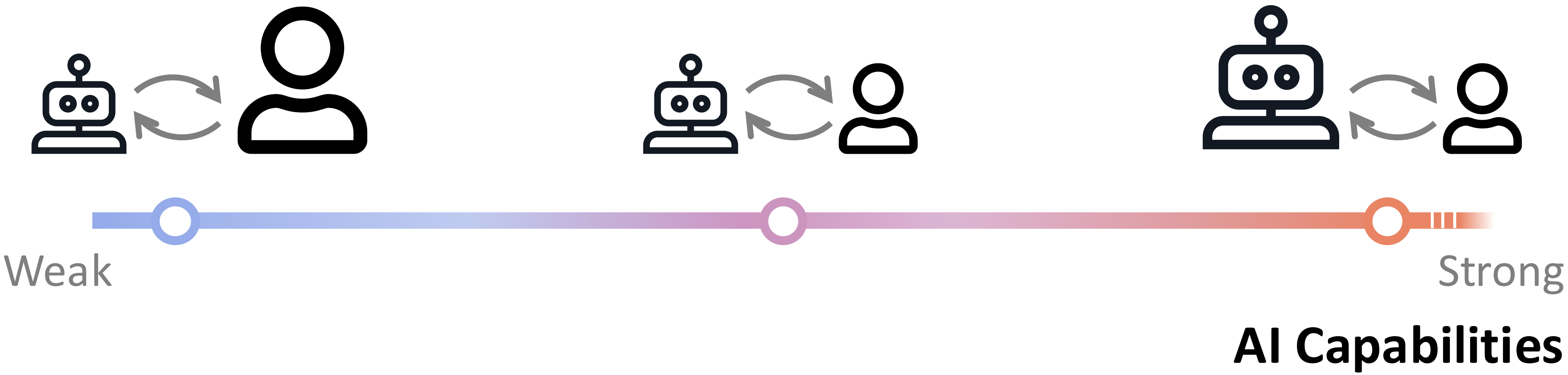
I call this approach **"human-centered A.I."** It consists of three goals that can help responsibly guide the development of intelligent machines.

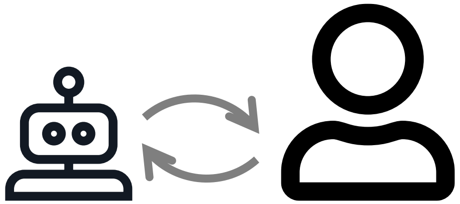


AI Capabilities


Weak
Strong
AI Capabilities

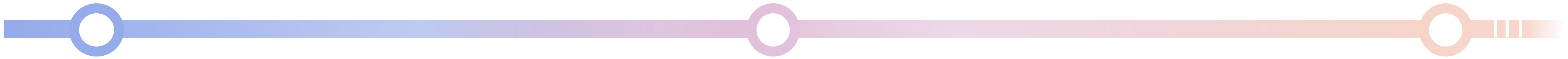
My research explores how we can design visualization-empowered Human-AI interactions that support diverse data tasks.





AI: distill knowledge

Humans: expert in making decisions



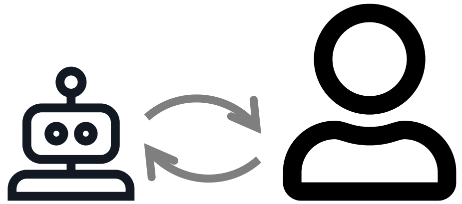
Weak

Strong

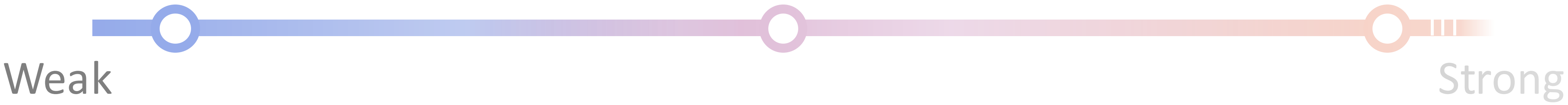
AI Capabilities

Emotion-Oriented Visual Summarization of Classroom Videos

TVCG'20



Haipeng Zeng, Xinhuan Shu, Yanbang Wang, Yong Wang, Liguo Zhang, Ting-Chuen Pong, Huamin Qu



AI Capabilities

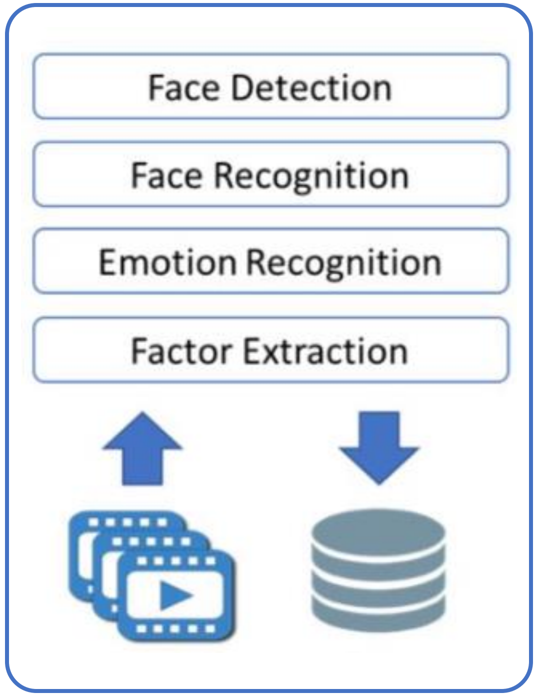
Emotion analysis in classroom videos

Exploring students' emotion can help both teachers and parents know about students' learning status and further help teachers improve teaching.

It is not easy for teachers to quickly capture and explore many students' emotions in the classroom.

How to carry out **efficient**, **informative**, **reliable** emotion analysis?

AI | VIS | Human



AI

VIS

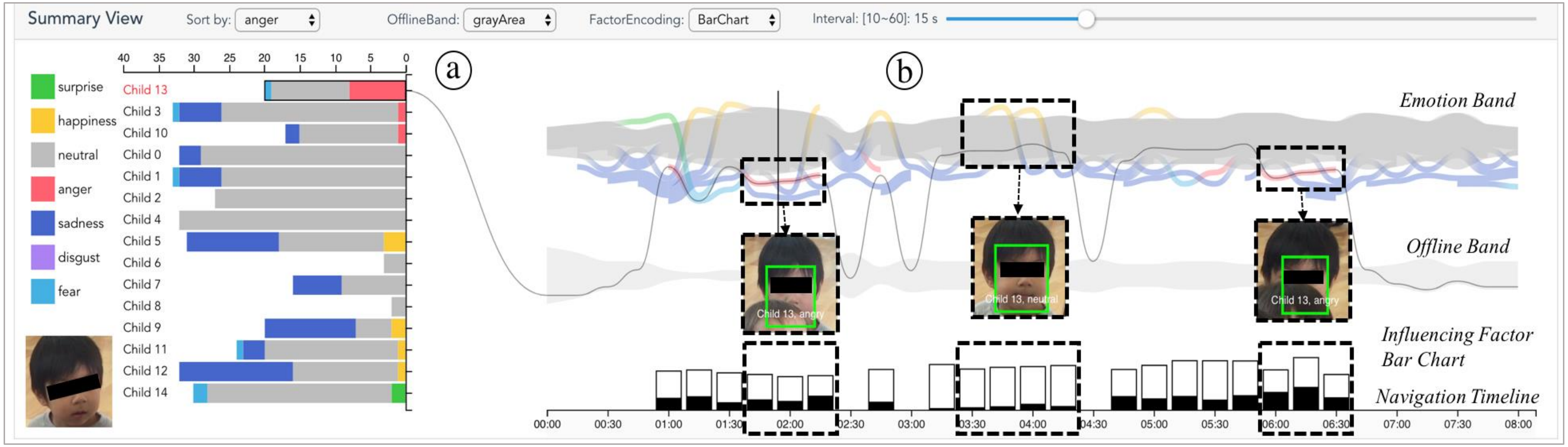
Human

AI recognizes emotions of individual students, but the model output has uncertainties.

Visualization enhances understanding for insight discovery

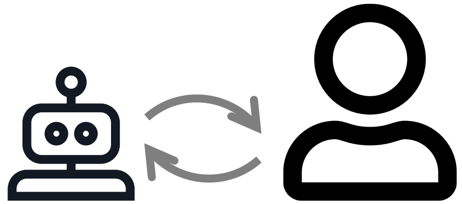
Teachers explore students' engagement status

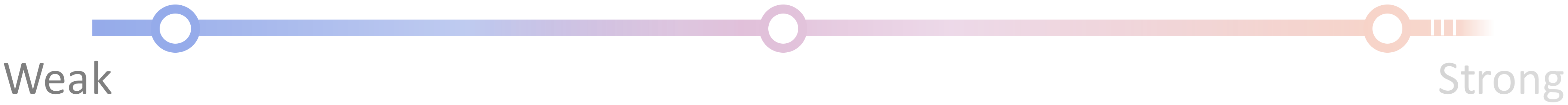
Misidentified anger emotion



Lessons Learned

- Integrate the model uncertainty into emotion analysis
- Model performance heavily relies on the representative-ness of the training datasets

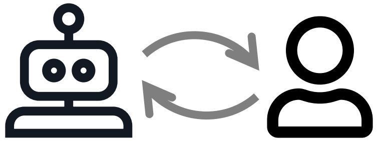


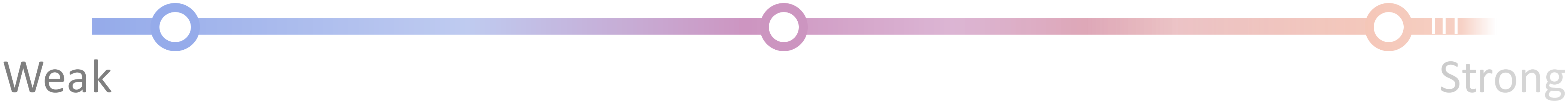


AI Capabilities

Human-AI Co-creation

of visualizations



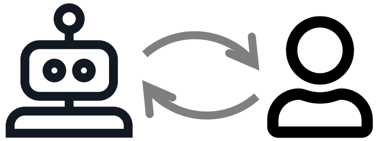


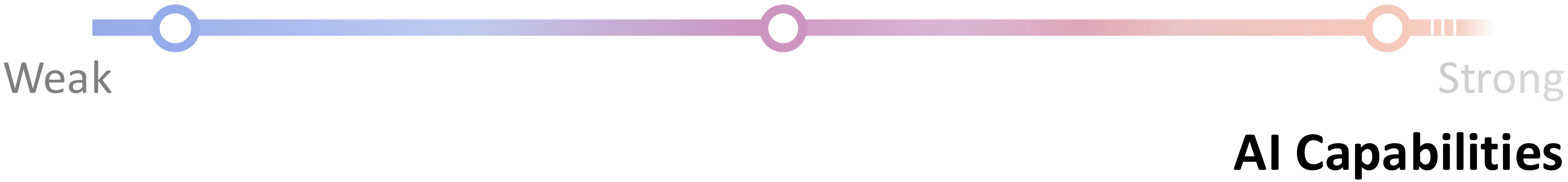
AI Capabilities

Automatic Generation of Metaphoric Glyph-based Visualization

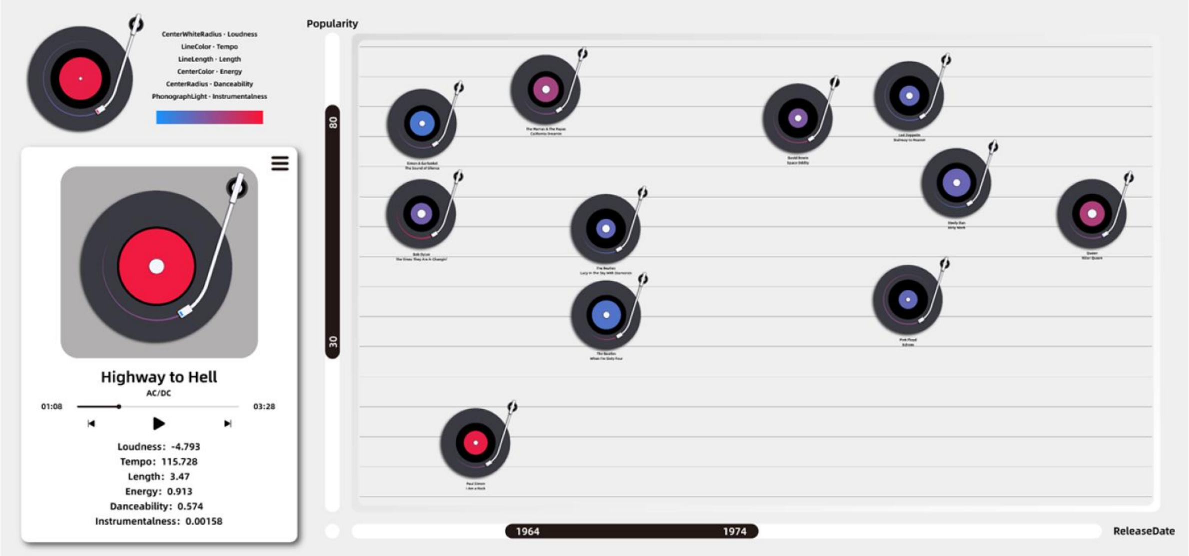
VIS 2022

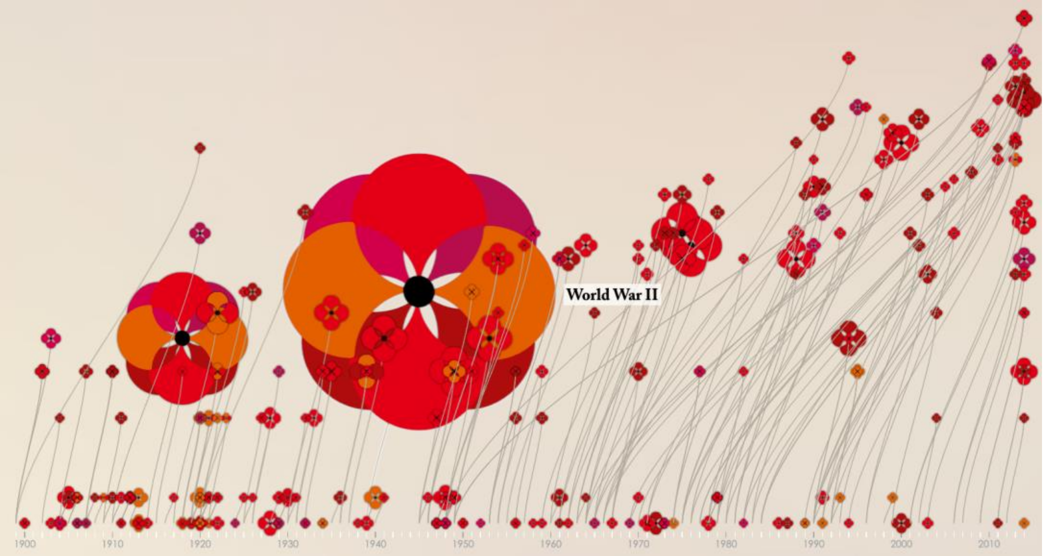
Lu Ying, **Xinhuan Shu**, Dazhen Deng, Yuchen Yang, Tan Tang, Lingyun Yu, Yingcai Wu





Metaphoric Glyph-based Visualization (MGV)





How to Create MGVs?

Entry number	Primary Type	Secondary Type	Base Attack	Base Defense	Base HP	Special Attack	Special Defense	Base Speed	Height of Objects	Weight of Objects
70	grass	poison	90	50	65	85	45	55	6.4	1
49	bug	poison	65	60	70	90	75	90	12.5	1.5
83	normal	flying	90	55	52	58	62	60	15	0.8
71	grass	poison	105	65	80	100	70	70	15.5	1.7
45	grass	poison	80	85	75	110	90	50	18.6	1.2
48	bug	poison	55	50	60	40	55	45	30	1
12	bug	flying	45	50	60	90	80	70	32	1.1
22	normal	flying	90	65	65	61	61	100	38	1.2
84	normal	flying	85	45	35	35	35	75	39.2	1.4
94	ghost	poison	65	80	60	170	95	130	40.5	1.5
72	water	poison	40	35	40	50	100	70	45.5	0.9
62	water	fighting	95	95	90	70	90	70	54	1.3
42	poison	flying	80	70	75	65	75	90	55	1.6
34	poison	ground	102	77	81	85	75	85	62	1.4

Pokemon data

How to Create MGVs?

Challenge #1: *How to select an appropriate visual metaphor?*

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Pokemon data

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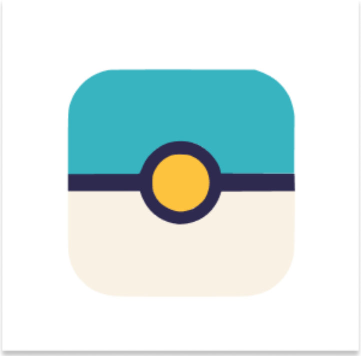

How to Create MGVs?

Challenge #2: *How to embed metaphors into glyph-based visualization design?*

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Pokemon data

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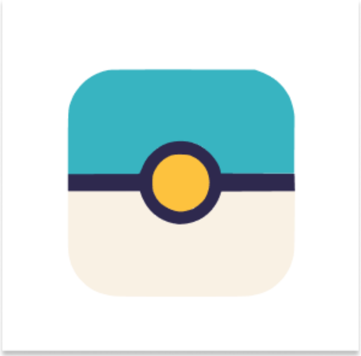

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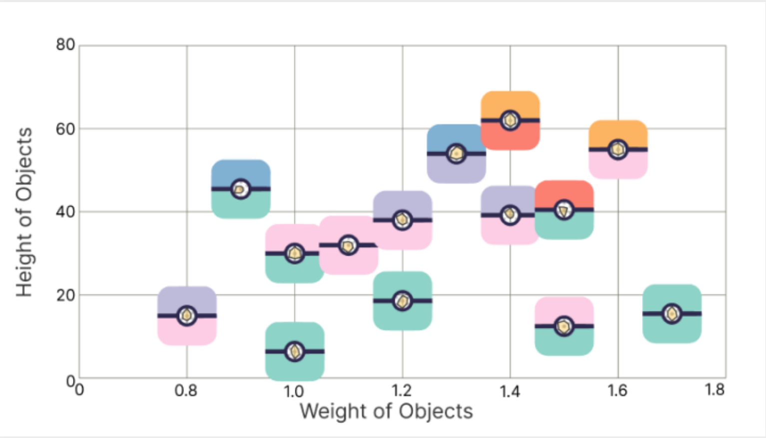

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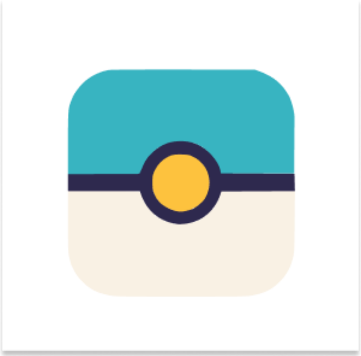

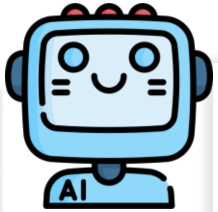

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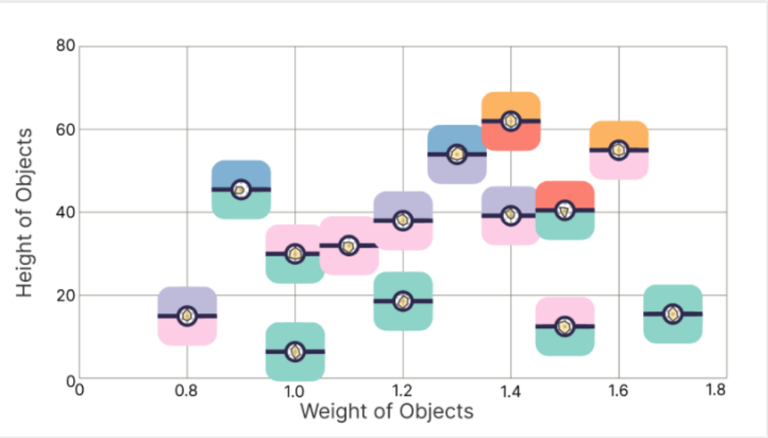


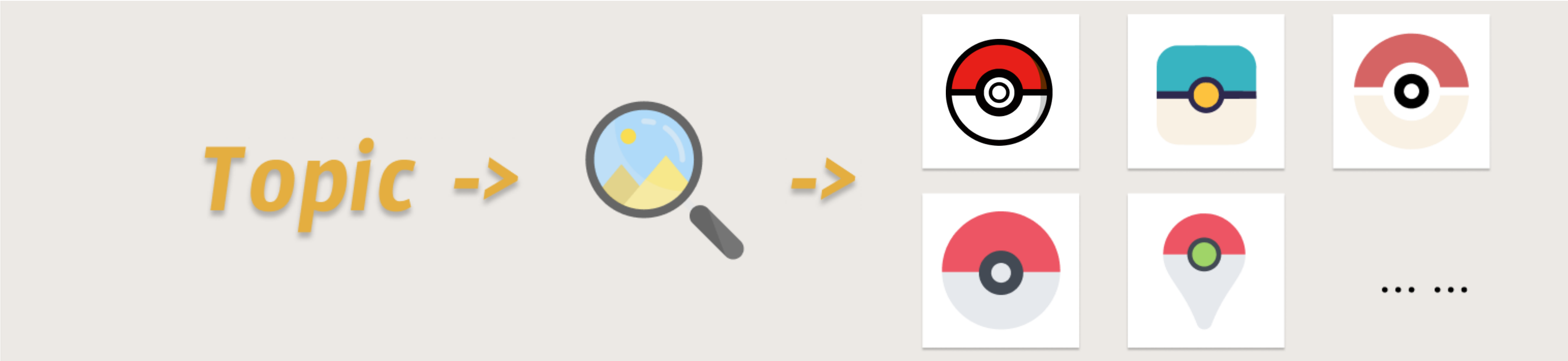
MGV Generation Model

Select Metaphoric Images → Construct → Render

MGV Generation Model

Select Metaphoric Images → Construct → Render

1. It is **semantically** related to the data.
2. It is a **vector image** with a relatively **simple** structure.



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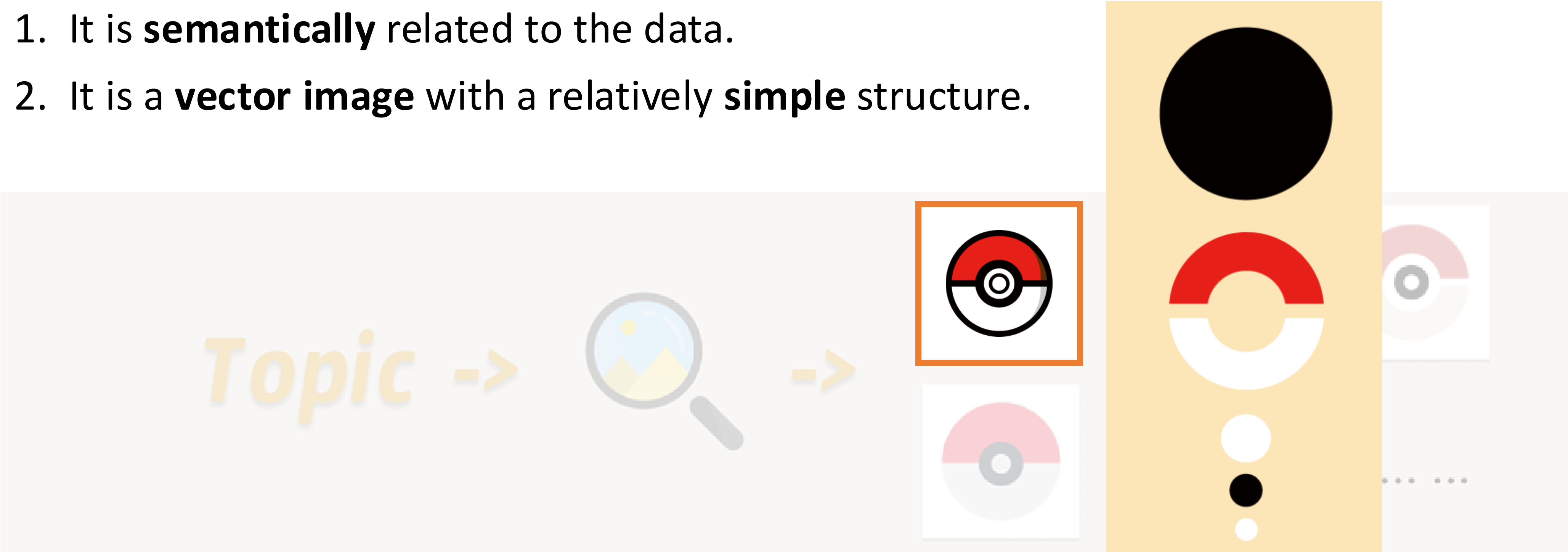
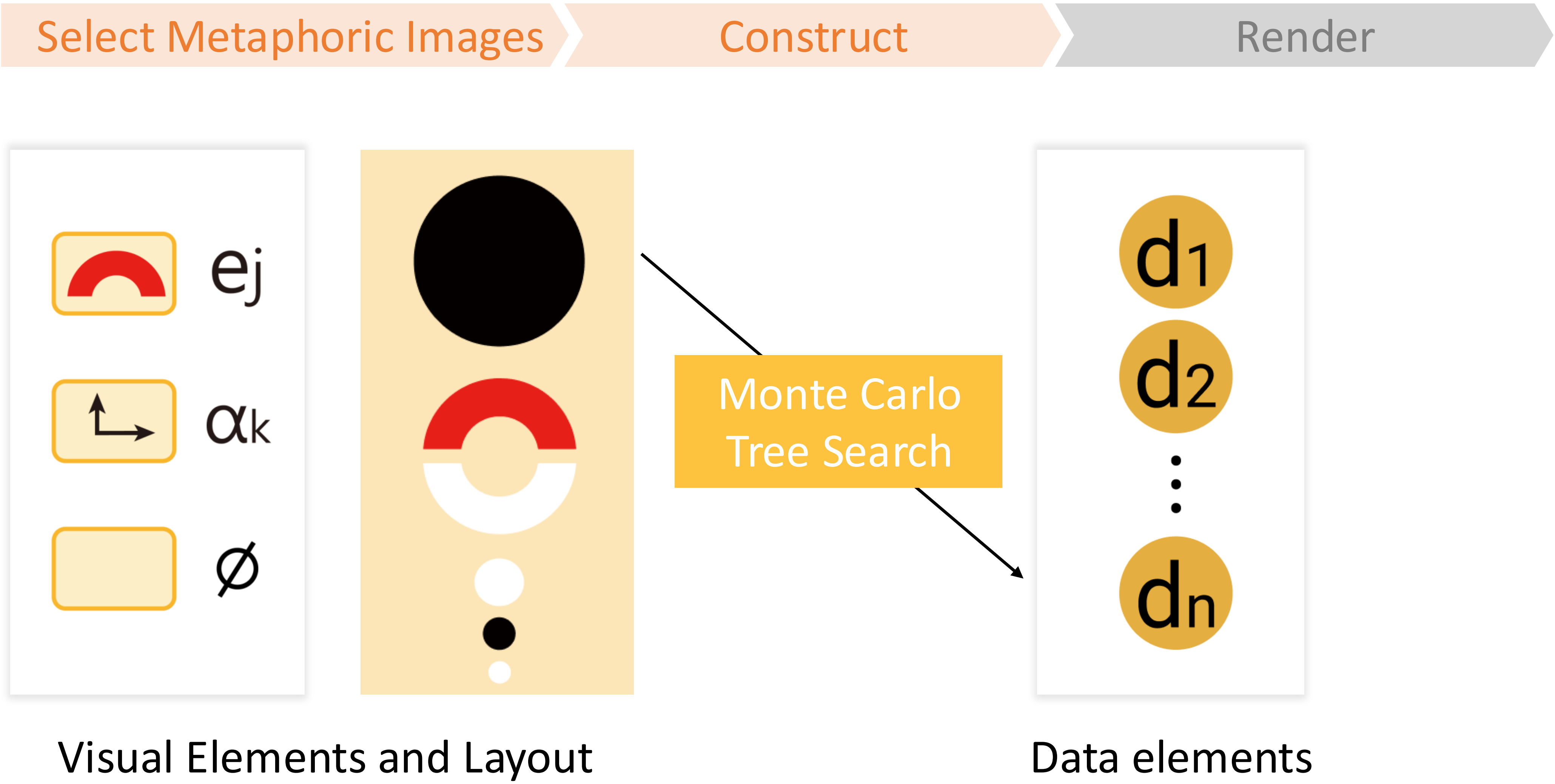


MGV Generation Model



MGV Generation Model

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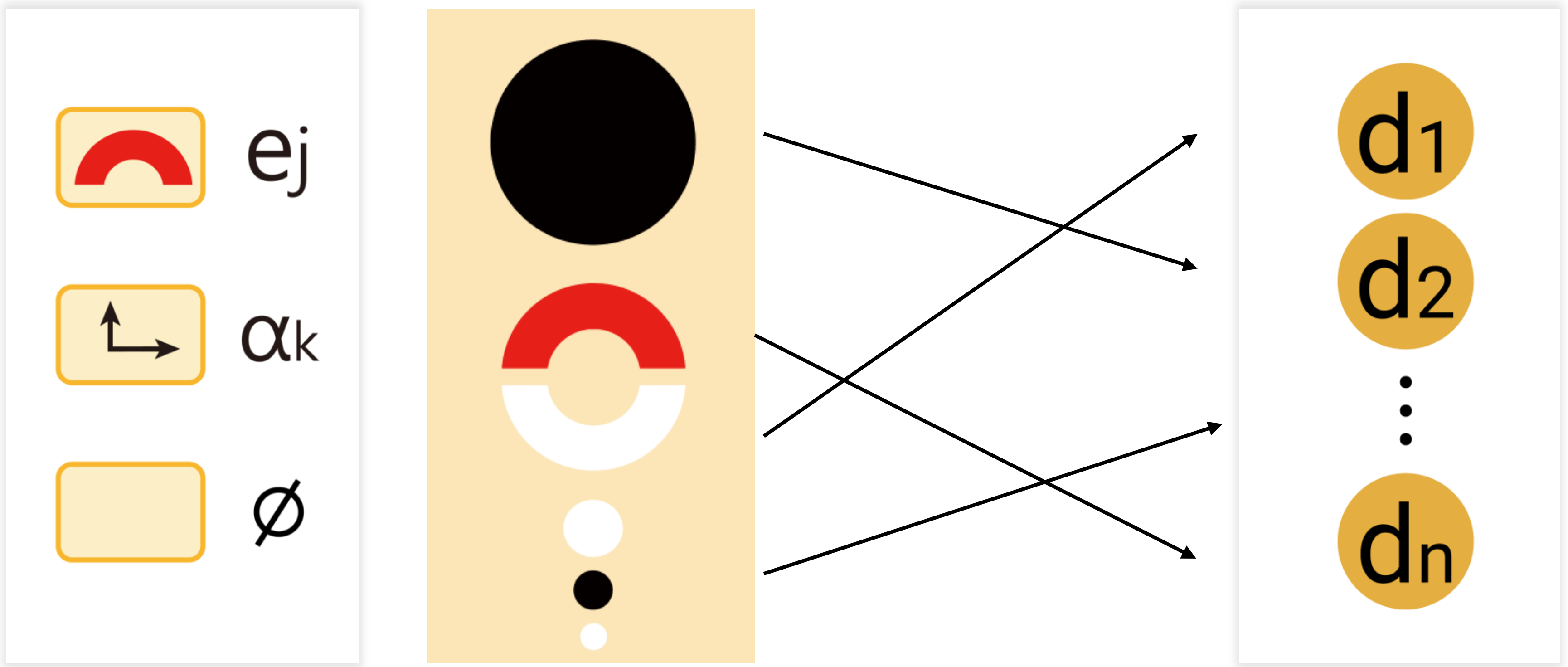
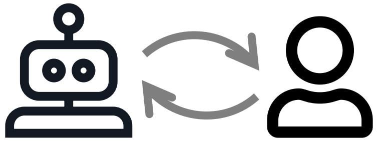
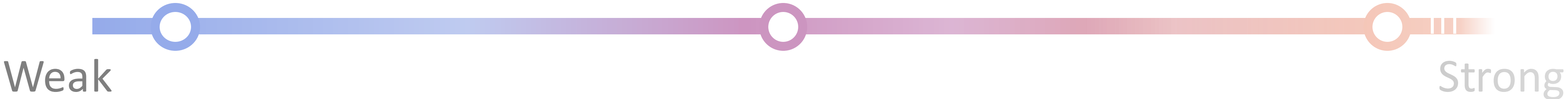


Lessons Learned

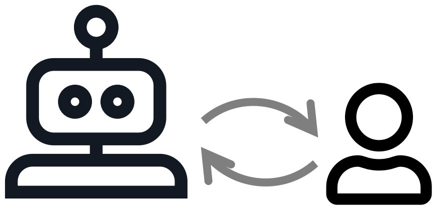
- Assigning the labor-intensive part to the machine and providing the connectors of subjective decisions to human beings.
- AI can enumerate possibilities, which serendipitously result in promising design.

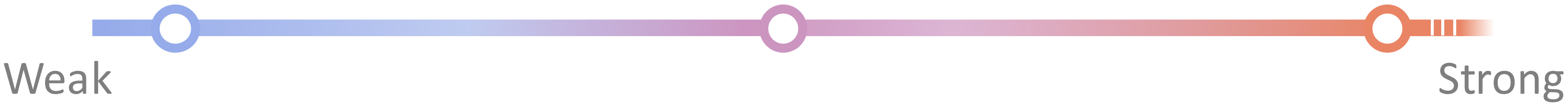




AI Capabilities

Humans may learn from **AI**



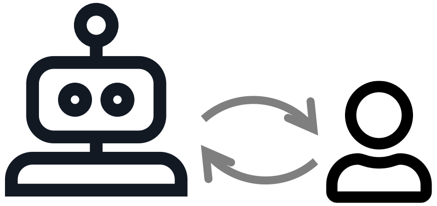


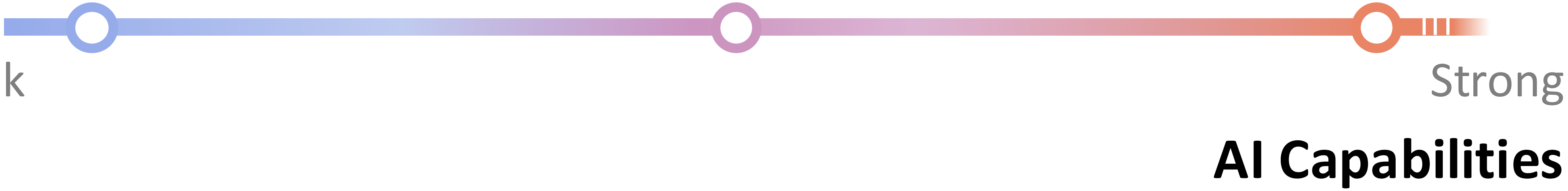
AI Capabilities

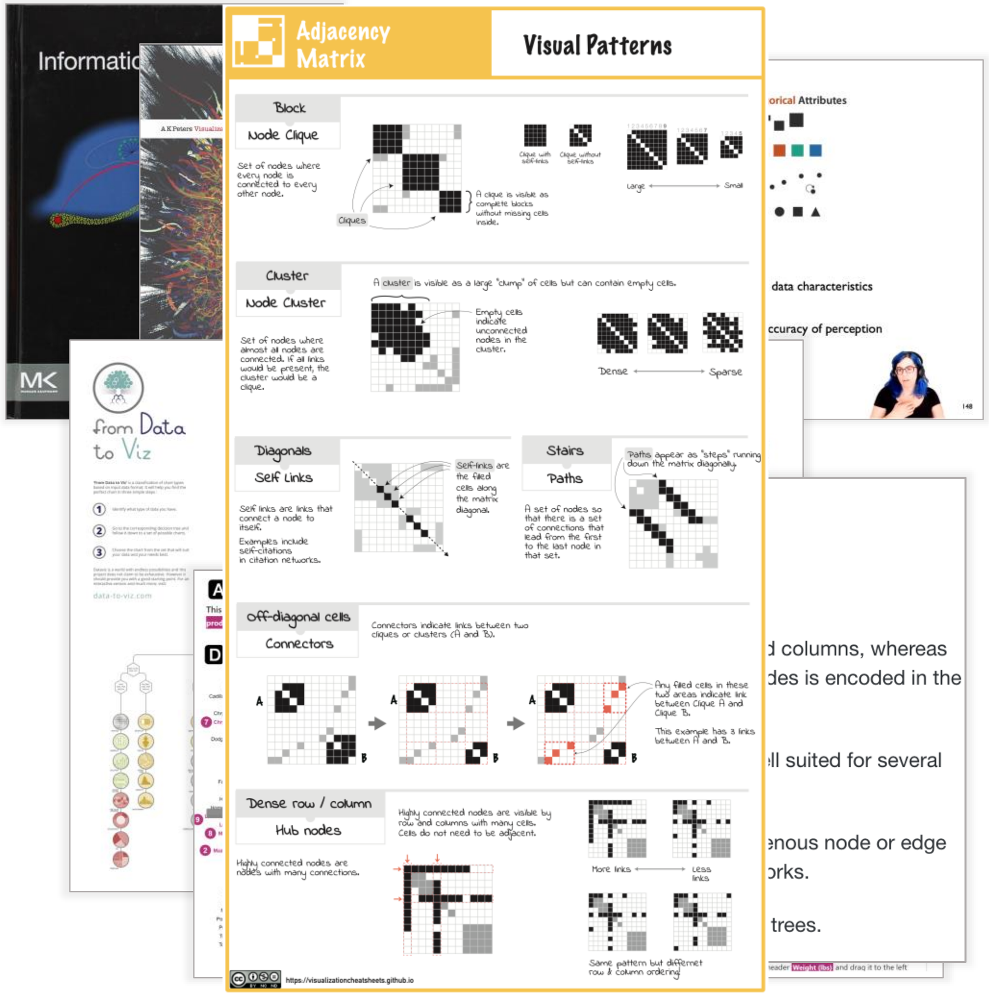
Interactive Pattern Explanation for Network Visualizations

VIS 2024

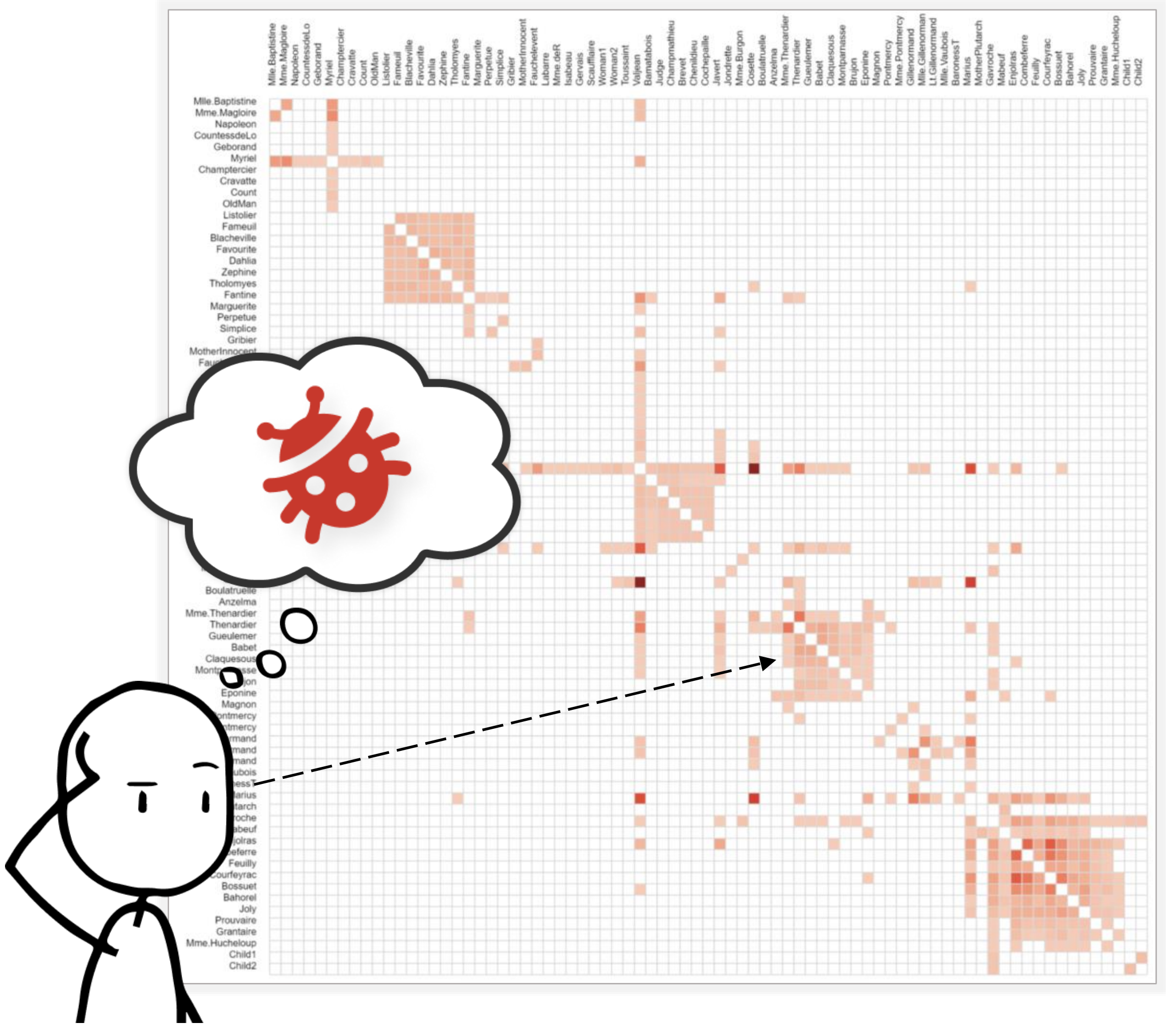
Xinhuan Shu, Alexis Pister, Junxiu Tang,
Fanny Chevalier, Benjamin Bach



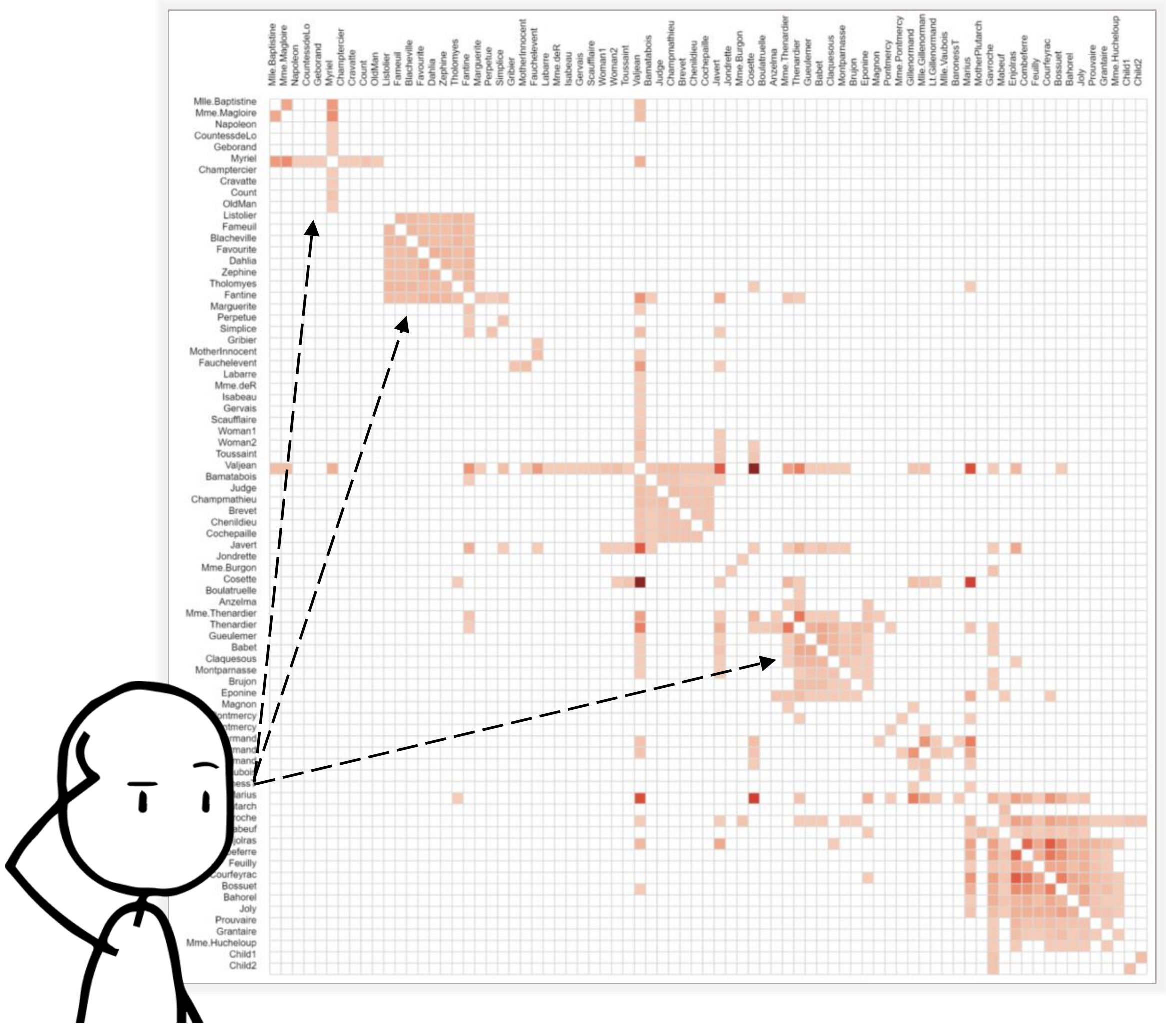


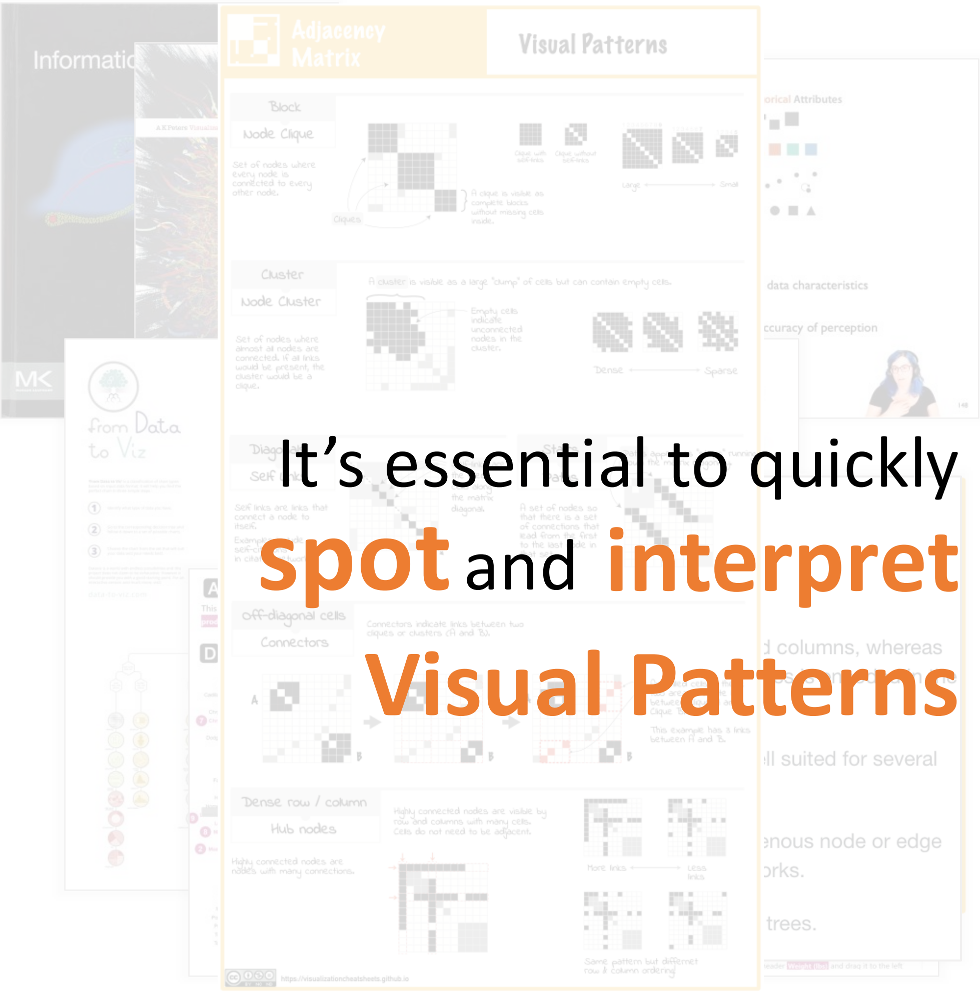


Information visualization: perception for design [Ware, 2019]
Visualization analysis and design [Munzner, 2014]
From data to viz.
Design and Comparative Evaluation of Visualization Onboarding Methods [Stoiber et al., 2021]
The State of the Art in Visualizing Multivariate Networks[Nobre et al. 2019]



Informatic
Adjacency Matrix
Visual Patterns
from Data to Viz





It's essential to quickly **spot** and **interpret** **Visual Patterns**

Visualization Literacy

"the ability to confidently use a given data visualization to translate questions specified in the ***data domain*** *into visual queries in the* ***visual domain****, as well as* **interpret Visual Patterns** *in the visual domain as properties in the data domain."*

A principled way of assessing visualization literacy [Boy et al. 2014]

"the ability to make meaning from and ***interpret patterns****, trends, and correlations in visual representations of data"*

Data visualization literacy [Börner et al. 2019]

"detects salient ***visual patterns****, translates them into conceptual information structures"*

Seeking patterns of visual pattern discovery for knowledge building [Andrienko et al. 2022]

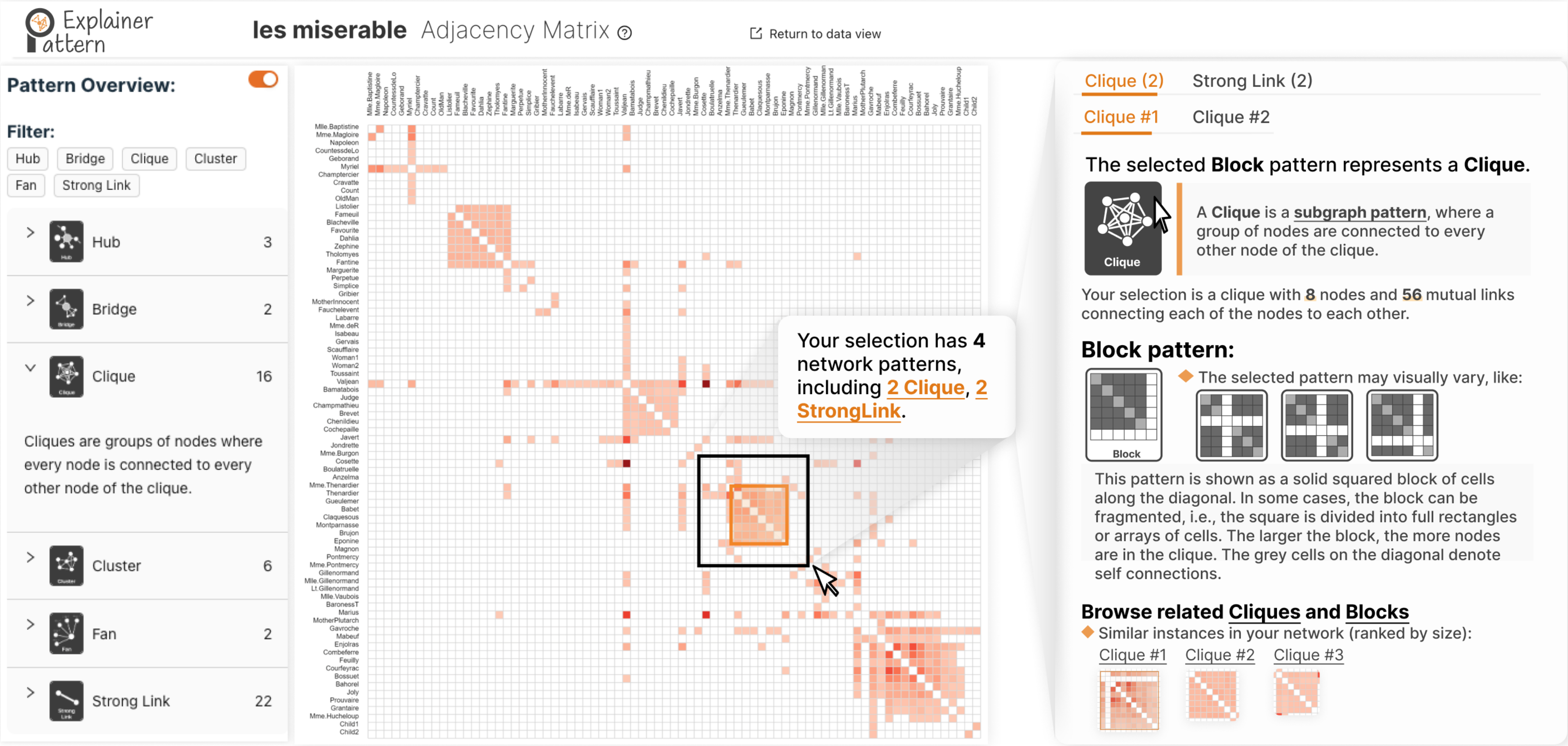
Research problem

How to support people to quickly

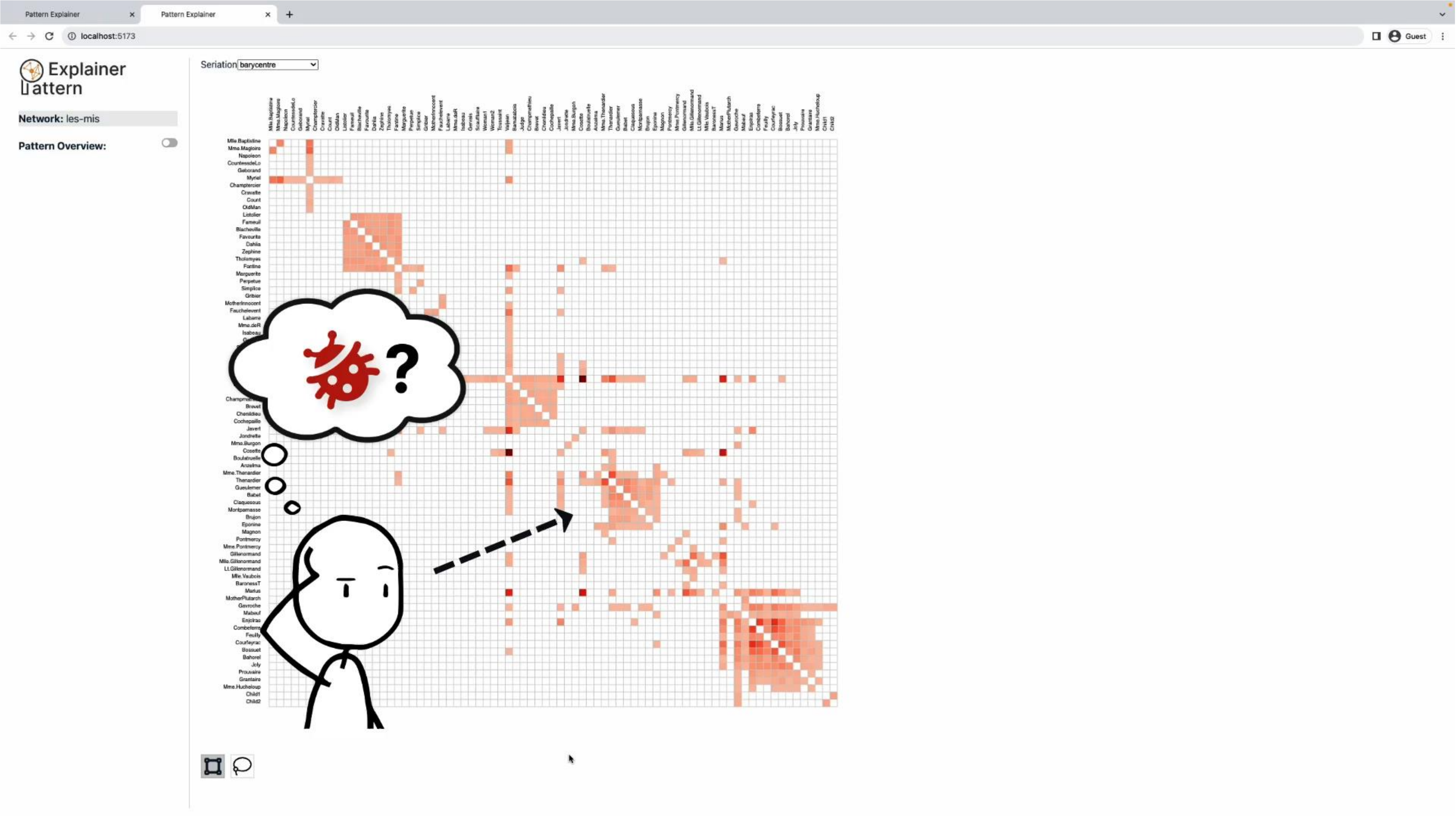
spot and **interpret Visual Patterns**

Interactive Pattern Explanations

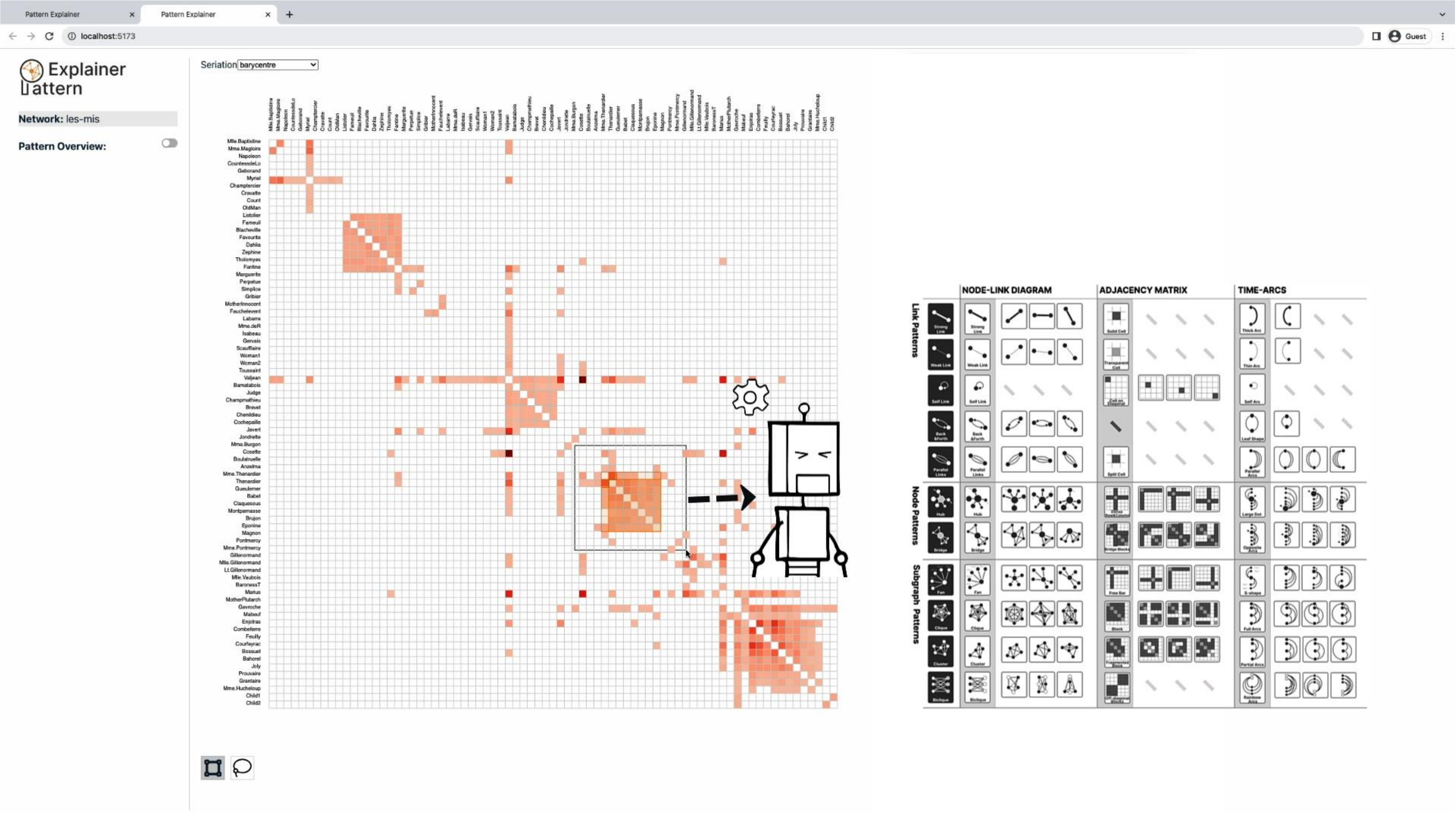
Explaining visual patterns and their data patterns on-demand in user-defined parts of visualization.



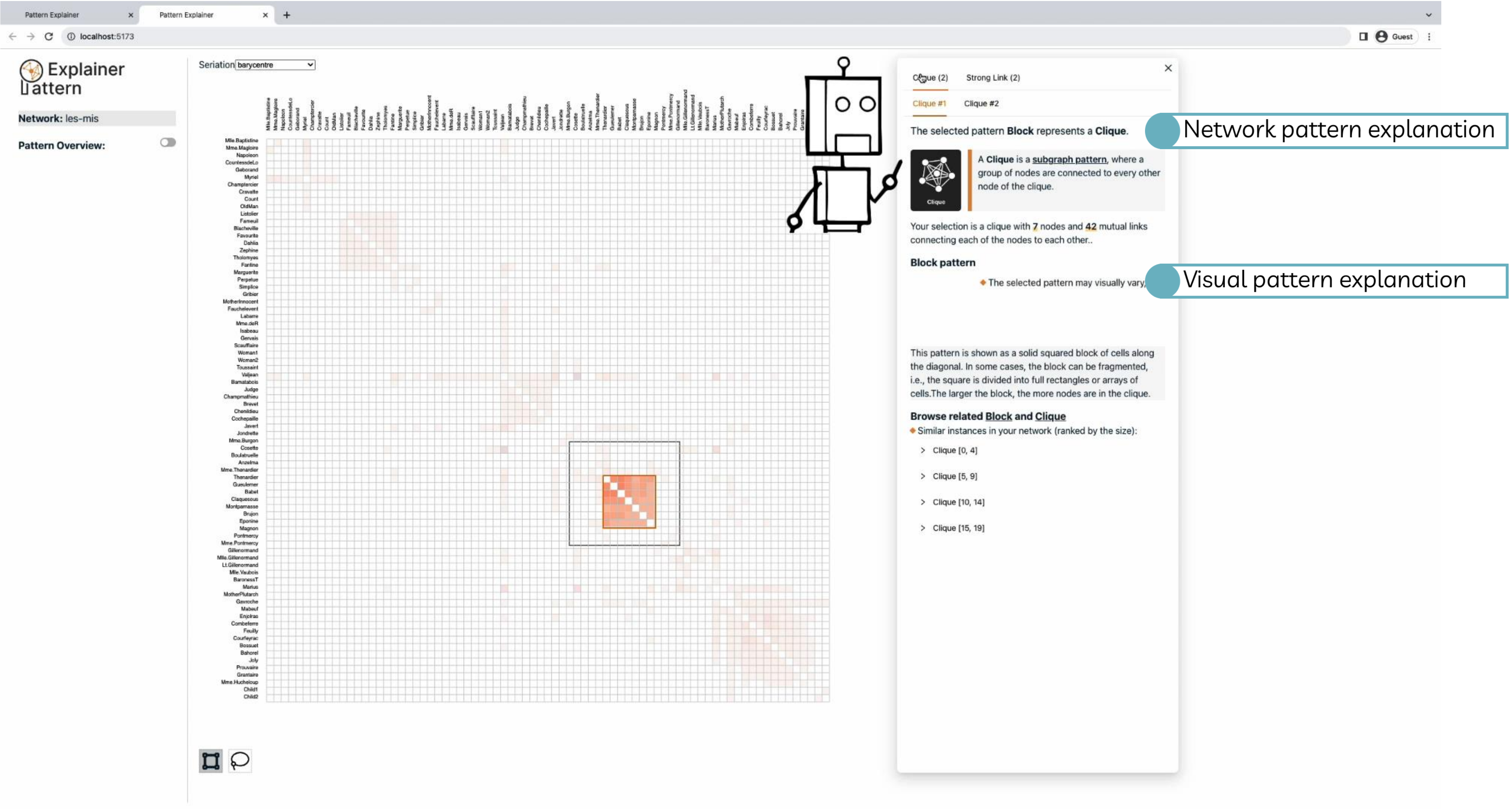
Interactive Pattern Explanations



Interactive Pattern Explanations



Interactive Pattern Explanations



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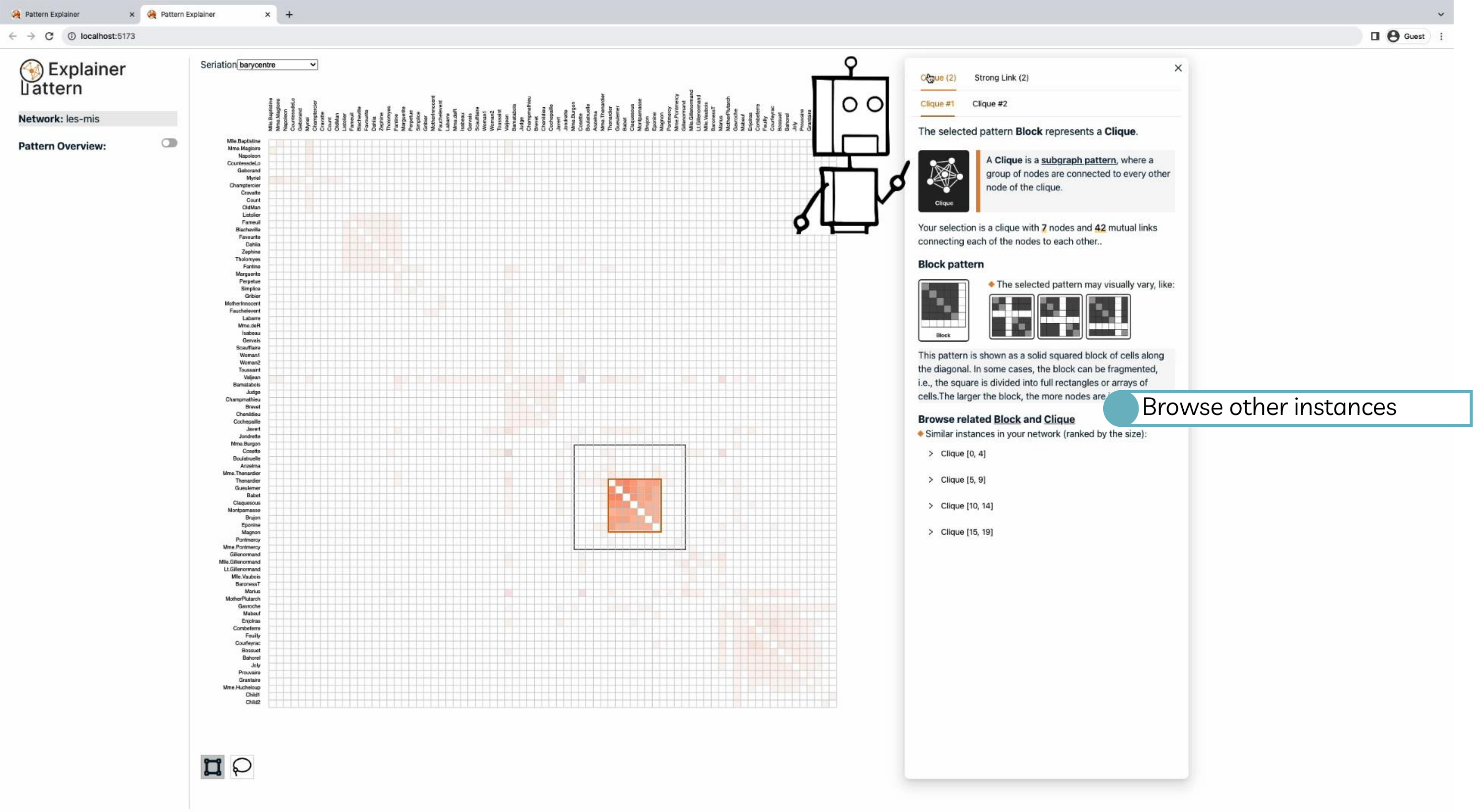
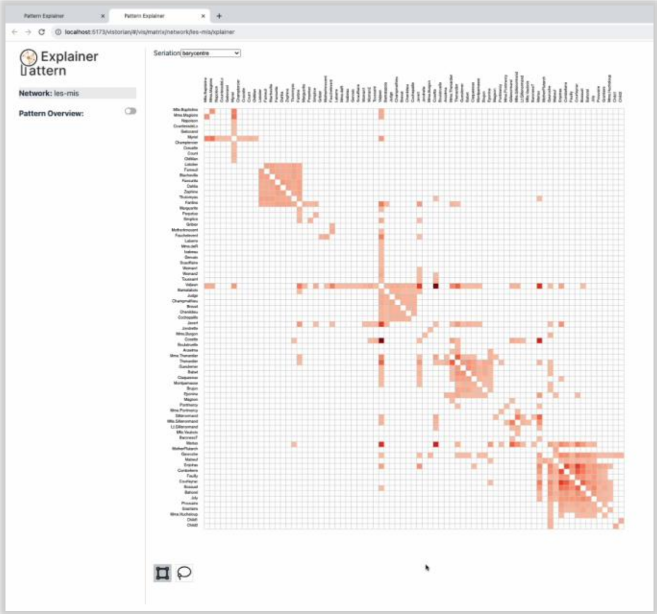


Evaluation

- Qualitative Study:
  - We ran a within-subject design with 12 participants, asking them to learn and interpret three network visualizations in an open-ended way.
- Quantitative Study:
  - We ran a between-subject design with 20 participants to measure how many patterns people can accurately identify after learning adjacency matrices.

Text-only

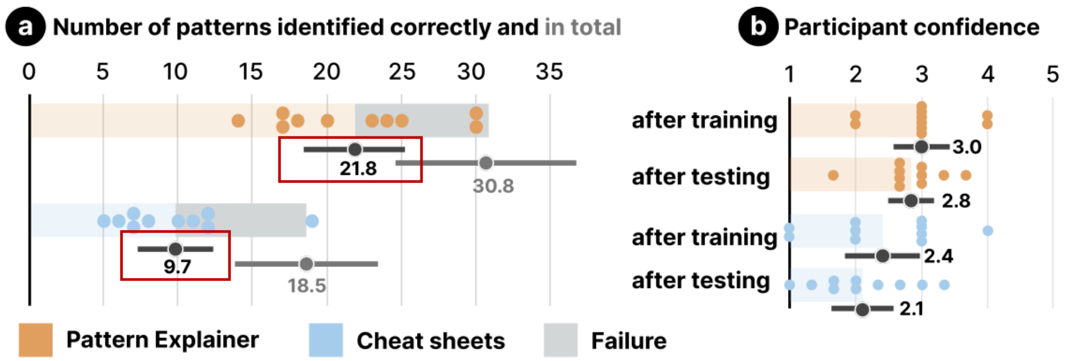
Cheatsheet



Pattern Explainer

Evaluation

- Results:
  - Increase the number of patterns people identify correctly.



Condition	Sum	#SL	#Hub	#Bridge	#Fan	#Clique	#Cluster
Pattern Explainer	**21.8**	1.9	2.4	2.7	1.1	8.0	5.7
Cheat sheets	**9.7**	1.3	0.9	0.7	0.7	3.6	2.5

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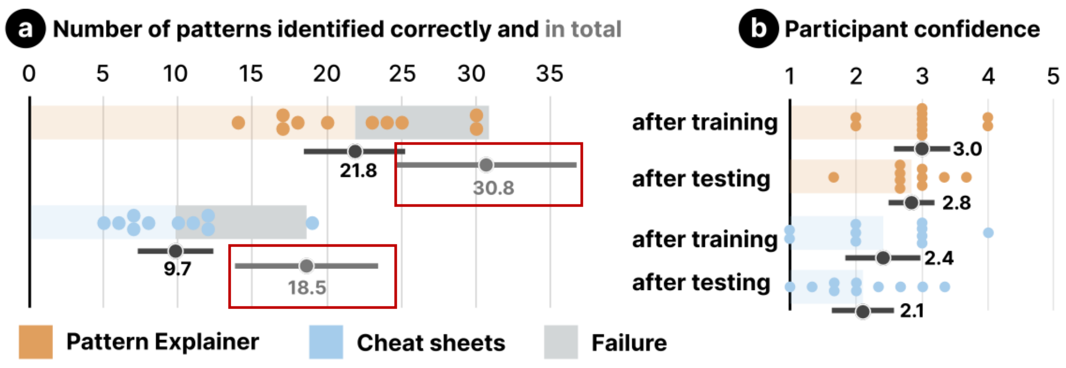
- Results:
  - Increase the number of patterns people identify correctly.



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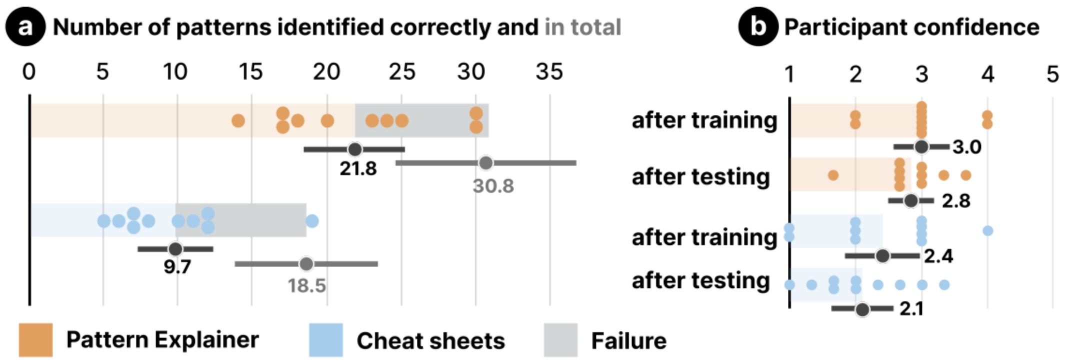

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Evaluation

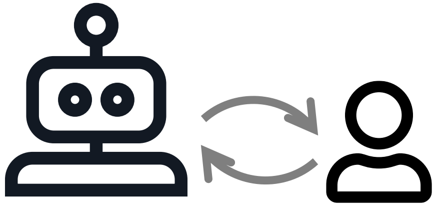
- Results:
  - Increase the number of patterns people identify correctly.
  - Appreciate the in-situ and on-the-fly explanations.

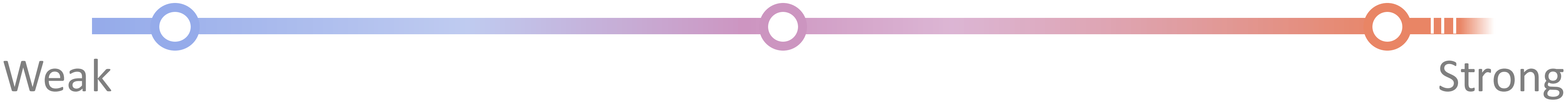
"Interactive pattern explanations put the theoretic concepts into practice."

"Cheat sheets could not directly apply to the visualization. I got more confused about whether my understanding of this cheat sheet was right."

Lessons Learned

- In-context and on-the-fly explanations can help novices improve visualization (data) literacy.
- Personalized, guided, and progressive tutorials are promising for AI-assisted education.



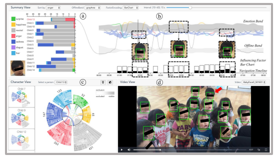


AI Capabilities

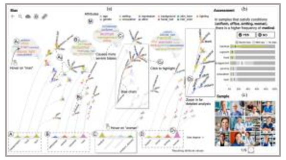
MetaGlyph
VIS'22

WonderFlow
TVCG'23

RouteFlow
CHI'25
Best Paper



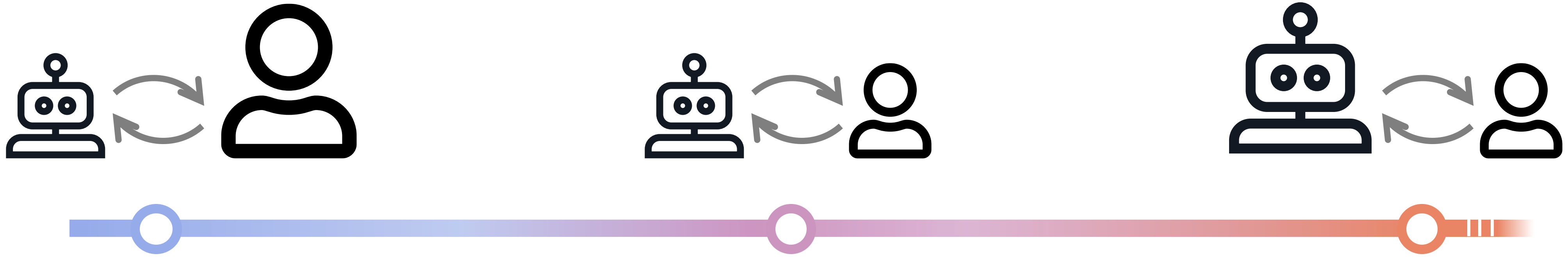
EmotionCues
TVCG'20



BiasField
Under review

Pattern Explanation
VIS'24

FretMate
IUI'24



Weak

Strong

AI Capabilities

From Data to Dialog: **Visualization-empowered Human-AI Collaboration**

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Lecturer @ Newcastle University

Data Visualisation 📊 / Human-Computer Interaction 🖥 / Data-driven Storytelling 🖊