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HKUST VIS

Transforming Graph Visualization Through AI and Human-AI Collaboration

Huamin Qu

Hong Kong University of Science and Technology



Hong Kong University of Science and Technology (HKUST)



HKUST VisLab

The HKUST VisLab is dedicated to advancing the frontiers of visual analytics, driven by a passion for transformative research with far-reaching impact.

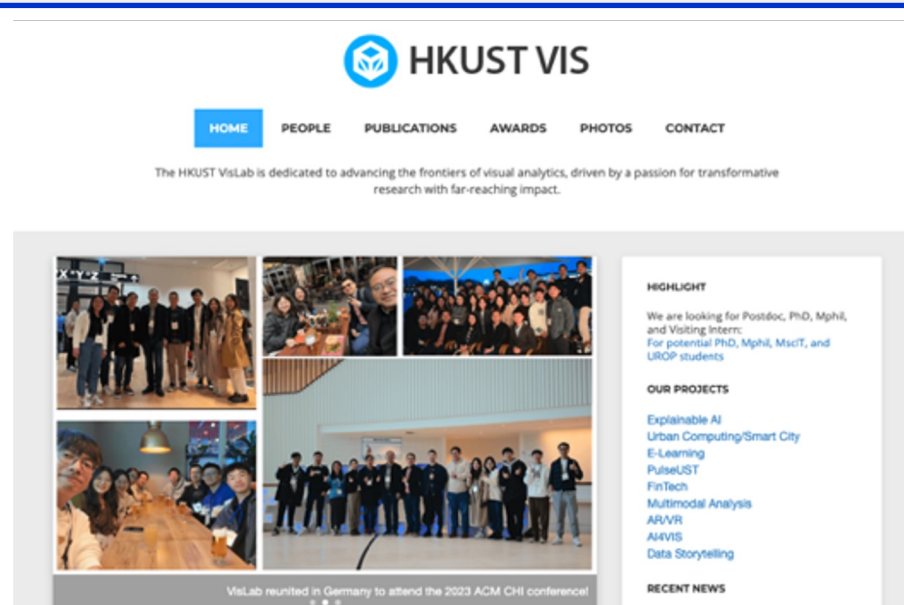
Big Data Analytics, Data Visualization, Visual Analytics, Human Computer Interaction, Explainable AI, AI for Vis, Urban Computing/Smart City, E-Learning, Social Media, Social Network/Graph, Fintech, Multimodal Human Communication, and eXtended Reality



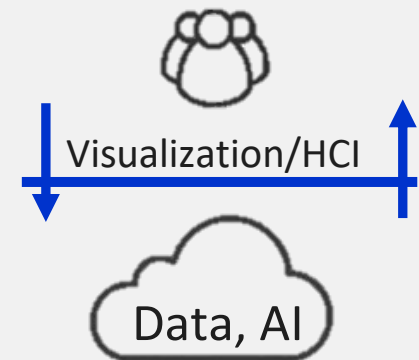
Huamin Qu (屈华民, 屈華民)

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Chair professor in the Department of Computer Science and Engineering (CSE)
The dean of the Academy of Interdisciplinary Studies (AIS)



<http://vis.cse.ust.hk/index.html>



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20th Anniversary

Rekindling Fond Memories,
Cherishing Classmate Bonds

重拾美好记忆 共怀同学之情

桃李春风一杯酒，江湖夜雨十年灯
你在哪里，VisLab就在哪里！

● Gieve George
● Lei Han
● Shuchang Xu
● Yujia He
● Yuzhe Shi
● Zichen Liu
● Barakeel Fansau Kamhous
● Leixian Shen
● Yihao Meng
● Zhonghua Sheng
● Rui Hu
● Ziwei Wu
● Xiaofu Sun
● Ka Yan Fung
● Yihan Hou
● Kentaro Takahira
● Haobo Li
● Xixin Chen
● Xiaofu Jin
● Rui Sheng
● Zhengyang Ma
● Yifan Cao
● Kento Shigyo
● Yanna Lin
● Liwenhan Xie
● Haotian Li
● Kam Kwai Wong
● Yu Ho Lo
● Jianben He
● Linping Yuan
● Zhihua Jin
● Yuzhe Jiang
● Wenchao Li
● Xian Xu
● Tong Wai
● Zezheng Feng
● Zhenhua Xu
● Furui Cheng
● Xingbo Wang
● Leni Yang
● Aoyi Wu
● Yifang Wang
● Dong Sun
● Xinhuan Shu
● Meng Xia-3
● Haipeng Zeng
● Qianwen Wang-1
● Yao Ming
● Qiaomu Shen
● Zhutian Chen-1
● Xuanwu Yue
● Mingqian Zhao
● Ke Xu
● Dongyu Liu-2
● Quan Li-3
● Xun Zhao
● Yuanzhe Chen
● Qing Chen
● Yun Wang
● Yong Wang-3
● Siwei Fu
● Yanhong Wu
● Wenchao Wu
● Yixian Zheng
● Panpan Xu
● Conglei Shi
● Jiansu Pu
● Nan Cao-14
● Weiwei Cui
● Yingcai Wu-34
● Hong Zhou
● Ming-Yuen Chan

● Hangxiao Zhu
● Fatenem Mirhosseini
● Yi Wen
● Pan Hao Liu
● Xianhao Liu
● Xicheng Wen
● Yuejiao Chen
● Longfei Chen
● Yang Ouyang
● Laixin Xie
● Manusha Karunathilaka
● Shaofan Ruan
● Songheng Zhang
● Ziqing Qian
● Yike Wang
● Jiazhe Wang
● Chuer Chen
● Yi He
● Jie Bao
● Chao Yuan
● Xueyang Wang
● Yi Guo
● Zui Chen
● Xingyu Lan
● Danding Shi
● Zhuochen Jin
● Shunan Guo
● Hongyi Cen
● Chuan Zhang
● Zihan Xu
● Yangtian Liu
● Yunfan Zhou
● Yuchen He
● Yuan Tian
● Zhongsu Luo
● Jining Yin
● Ji Ma
● Lingyu Meng
● Xiyu Meng
● Liqi Cheng
● Yanhong Wu
● Shuhan Liu
● Lu Ying
● Renzhong Li
● Kai Xiong
● Ran Chen
● Xiangtong Chu
● Yihong Wu
● Xiwai Cai
● Junxiu Tang
● Anqi Cao
● Shuainan Ye
● Sadia Rubab
● Dazhen Deng-1
● Zikun Deng
● Jachen Wang
● Ji Lan
● Li Weng-1
● Tan Tang-2
● Weichen Sun
● Zhao Liu

● Shifu Chen
● Zhenning Chen
● Hanze Jia
● Weichen Sun
● Zhao Liu

Huamin Qu-72
(Total: 138)

PhD (6) :

USA (6) :

1. Dongyu Liu (刘冬煜): UC Davis, computer science department, tenure-track assistant professor, USA (<https://dongyu.tech>)
2. Qianwen Wang (汪倩雯): University of Minnesota, department of computer science and engineering, tenure-track assistant professor, USA (<https://qianwen.info>)
3. Zhutian Chen (陈竹天): University of Minnesota, department of computer science and engineering, tenure-track assistant professor, USA (<https://chenzhutian.org>)
4. Meng Xia (夏梦): Texas A&M University, Department of Computer Science and Engineering, tenure-track assistant professor, USA (<https://www.xiameng.org>)
5. Wai Tong (唐玮): Texas A&M University, School of Performance, Visualization & Fine Arts, tenure-track assistant professor, USA (<https://wtong2017.github.io/>)
6. Yifang Wang (王懿芳): Florida State University, Department of Computer Science, tenure-track assistant professor (<https://wangyifang.top/>)

UK (1)

7. Xinhuan Shu (舒欣欢): Newcastle University, School of Computing, Lecturer, UK (<https://shuxinhuan.github.io>)

Singapore (1)

1. Yong Wang (王勇): Nanyang Technological University, College of Computing and Data Science, tenure-track assistant professor, Singapore (<https://yong-wang.org>)

Hong Kong SAR, China (2)

1. Xian Xu (徐炯): Lingnan University, assistant professor, Department of Digital Arts and Creative Industries (<https://xxuxian.github.io>)

2. Linping Yuan (袁林萍): Hong Kong University of Science and Technology, research assistant professor, Department of Computer Science and Engineering (<https://yuanlinping.top/>)

Mainland China (12)

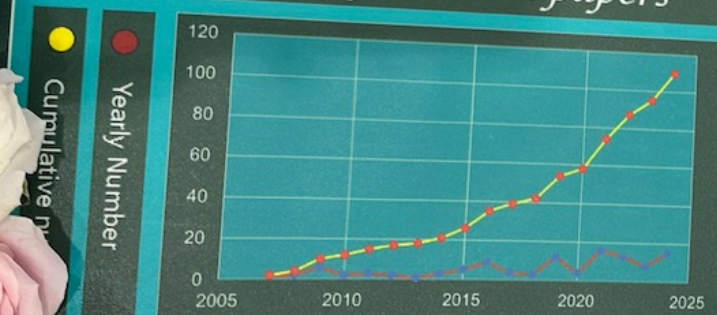
1. Yingcai Wu (巫英才): Professor, State Key Lab of CAD & CG, Zhejiang University Deputy Dean, College of Computer Science and Technology Zhejiang University, China (浙江大学计算机学院教授, 副院长) (<http://www.ycwu.org>)
2. Nan Cao (曹楠): the vice dean of Tongji College of Design and Innovation (Tongji D&I) and a professor at Tongji School of Software Engineering (同济大学设计创意学院教授, 副院长) (<https://nancao.org>)
3. Qing Chen (陈晴): associate professor at College of Design and Innovation, Tongji University (同济大学设计创意学院, 副教授) (<https://tjdi.tongji.edu.cn/TeacherDetail.do?id=5056&lang=en>)
4. Hong Zhou (周虹): Lecturer of the College of Computer Science and Software Engineering, Shenzhen University (深圳大学计算机与软件学院特聘副研究员) (<https://csse.szu.edu.cn/pages/user/index?id=537>)
5. Jiansu Pu (蒲剑苏): Professor at the Department of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China (电子科技大学计算机科学与工程学院教授) (<https://visjy.uestc.edu.cn/gmis/jcsjgl/dsfc/dsgrj/119177yxsh-08>)
6. Quan Li (李权): assistant professor at School of Information Science and Technology, ShanghaiTech University (上海科技大学信息科学与技术学院, 助理教授) (<https://faculty.sist.shanghaitech.edu.cn/liquan/>)
7. Haipeng Zeng (曾海鹏): Associate Professor at the School of Intelligent Systems Engineering, Sun Yat-sen University (SYSU) (中山大学智能工程学院, 副教授) (<http://www.zenghp.org>)
8. Qiaomu Shen (申乔木): Assistant Professor at Beijing Institute of Technology, Zhuhai (北京理工大学珠海, 助理教授) (<https://ai.bitzh.edu.cn/cs/info/1211/1611.htm>)
9. Siwei Fu (傅四维): ZJU100 Young Professor, School of Management, Zhejiang University (浙江大学管理学院百人计划研究员, 博士生导师) (<https://fusiwei339.bitbucket.io>) (<https://person.zju.edu.cn/siwei>)
10. Ke Xu (徐科): Tenure-track associate professor, School of Intelligence Science and Technology, Nanjing University (南京大学智能科学与技术学院准聘副教授) (<https://is.nju.edu.cn/xk/main.htm>)
11. Zezheng Feng (冯泽正): Associate Professor, School of Software Engineering, Northeastern University (东北大学软件学院软件工程系副教授) (<https://jerrodfeng.github.io/>)



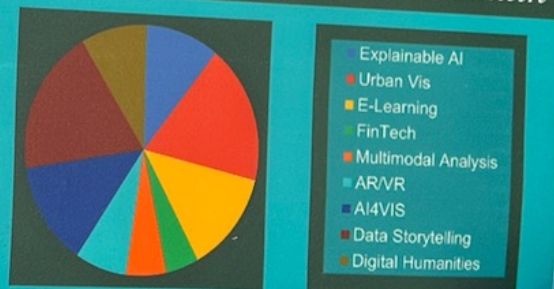
HKUST 20 VisLab Anniversary

Where we come from
where we have gone

Number of published papers



Distribution of Research Domain

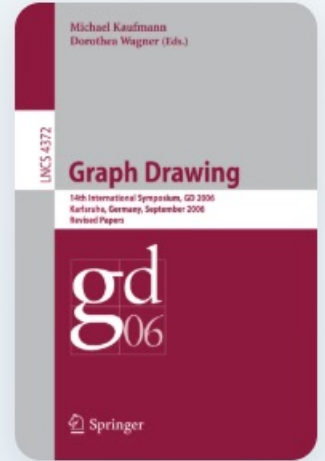


[Home](#) > [Graph Drawing](#) > Conference paper

Controllable and Progressive Edge Clustering for Large Networks

Conference paper

pp 399–404 | [Cite this conference paper](#)



Graph
Drawing
(GD 2006)

Huamin Qu, Hong Zhou & Yingcai Wu



Huamin Qu

[追蹤](#)

Chair Professor, Hong Kong University of Science and Technology

在 cse.ust.hk 的電子郵件地址已通過驗證 - [首頁](#)

[Data visualization](#) [Human-Computer Interaction](#) [Explainable AI](#) [E-Learning](#)

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標題	引用次數	年份
Textflow: Towards better understanding of evolving topics in text W Cui, S Liu, L Tan, C Shi, Y Song, Z Gao, H Qu, X Tong IEEE transactions on visualization and computer graphics 17 (12), 2412-2421	539	2011
Context preserving dynamic word cloud visualization W Cui, Y Wu, S Liu, F Wei, MX Zhou, H Qu 2010 IEEE Pacific Visualization Symposium (PacificVis), 121-128	476	2010
Geometry-based edge clustering for graph visualization W Cui, H Zhou, H Qu, PC Wong, X Li IEEE transactions on visualization and computer graphics 14 (6), 1277-1284	443	2008

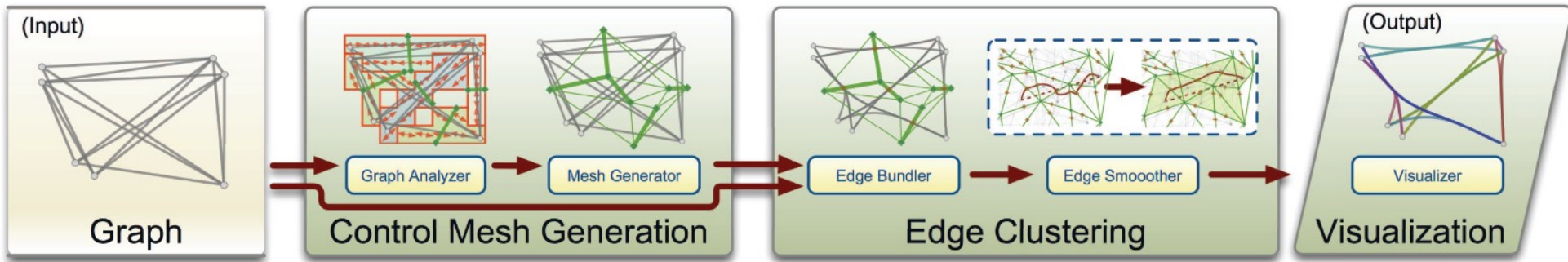


How to make graph visualization
less cluttered?

Geometry-Based Edge Clustering for Graph Visualization

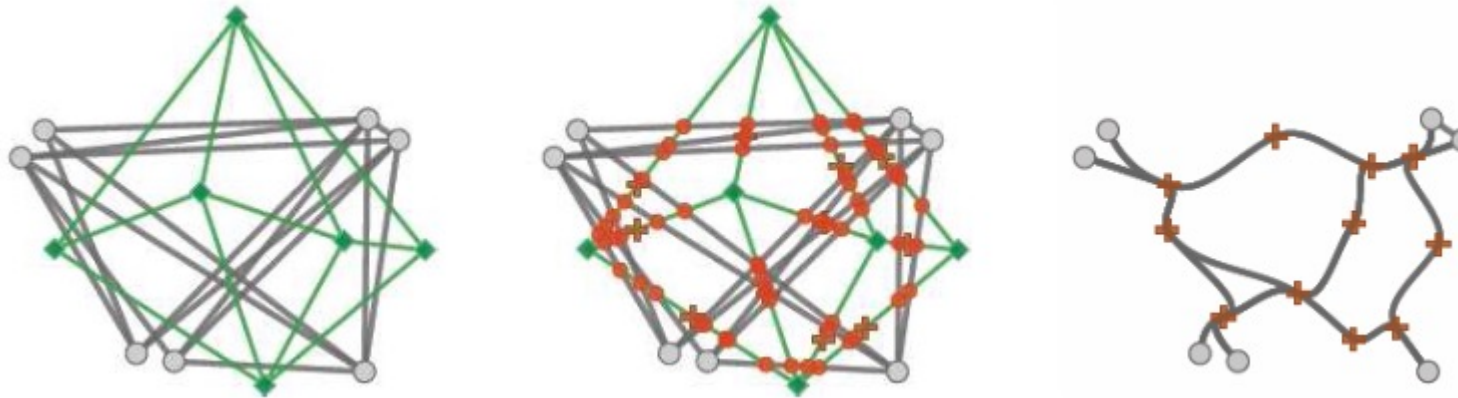
Weiwei Cui, Hong Zhou, Huamin Qu,
Pak Chung Wong, and Xiaoming Li

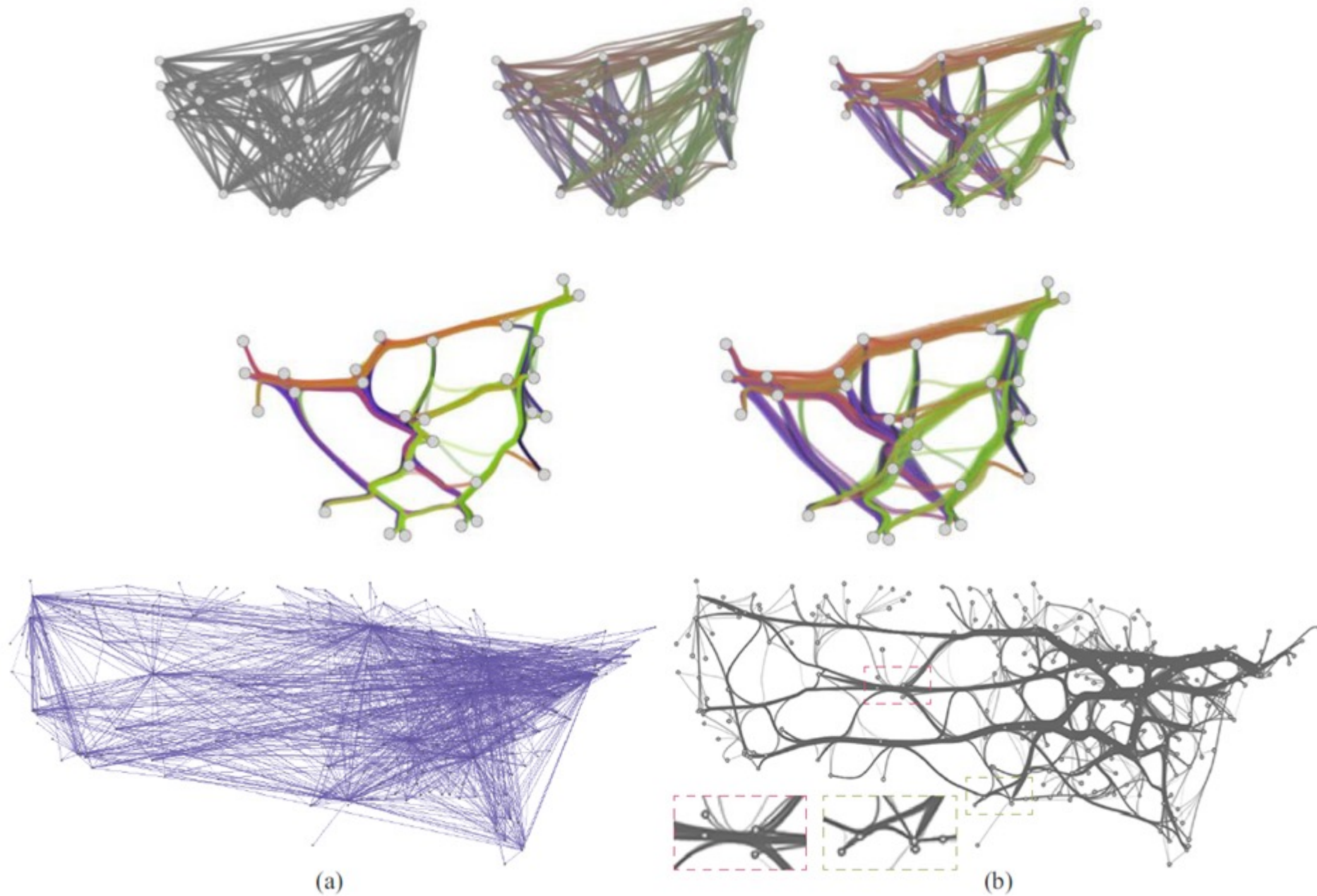
IEEE InfoVis 2008

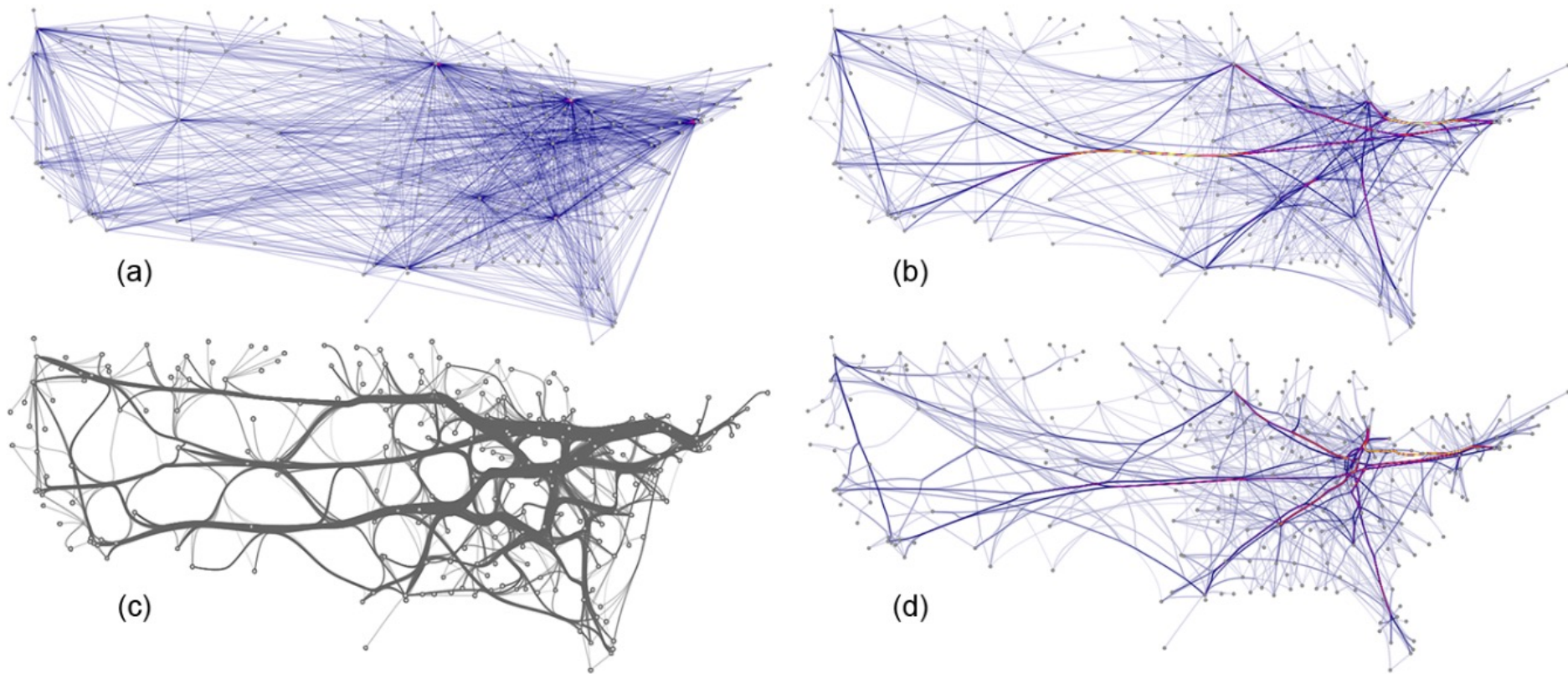


Control meshes are used to route curved edges

Control points: center of the intersection of graph edges and mesh





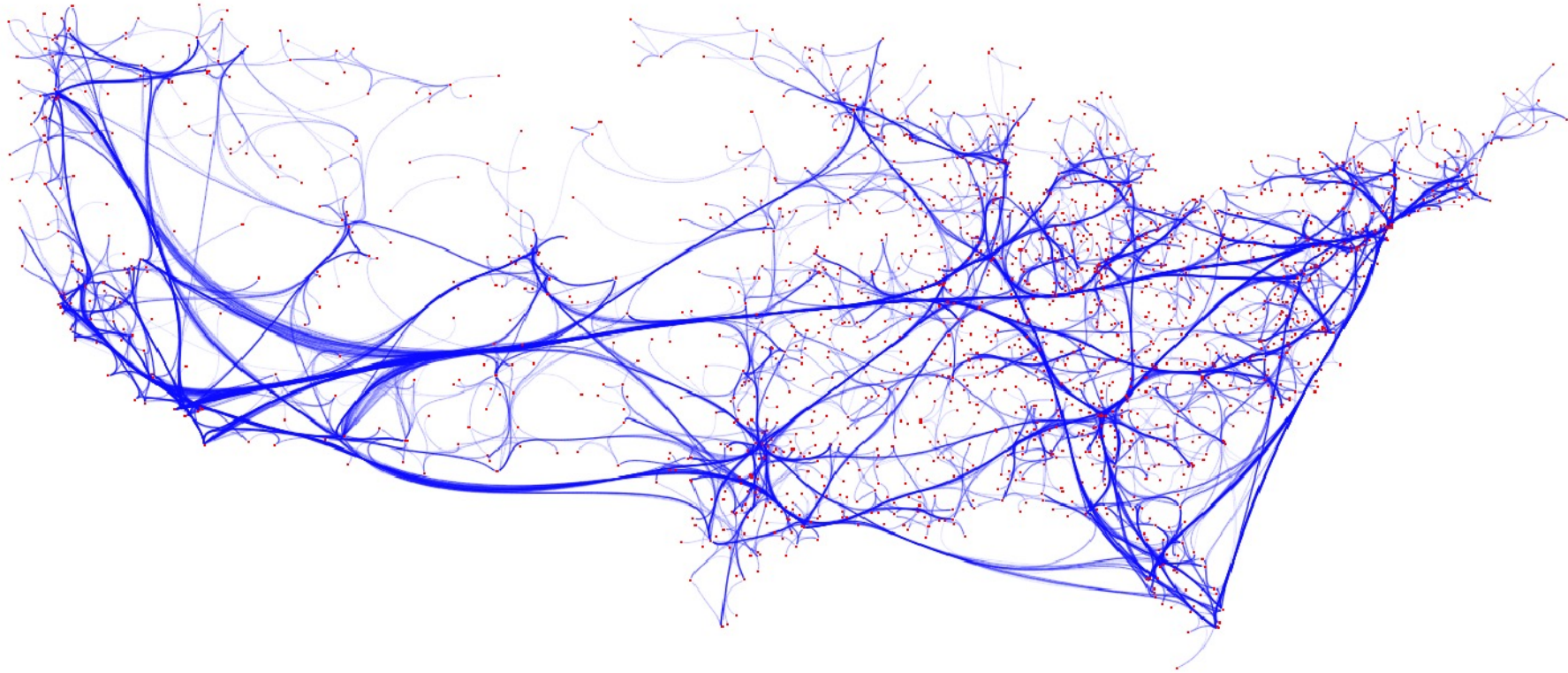


US airlines graph (235 nodes, 2101 edges)

(a) not bundled and bundled using (b) FDEB with inverse-linear model,
(c) GBEB, and (d) FDEB with inverse-quadratic model.

	Air Line
	graph
FDEB	18.8 s
GBEB	2.5 s

[Holten and Wijk EuroVis 2009]
Force-Directed Edge Bundling for Graph Visualization



Lambert et al. EuroVis 2010

Winding roads routing edges into bundles

Evaluation of Graph Sampling: A Visualization Perspective

Yanhong Wu, Nan Cao, Daniel Archambault, Qiaomu Shen, Huamin Qu, and Weiwei Cui

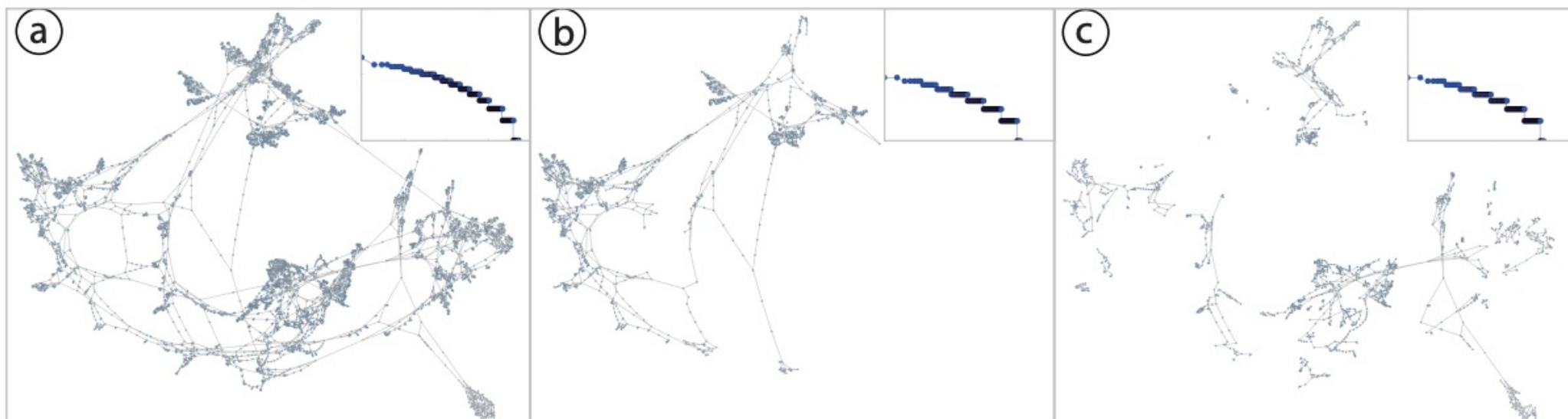


Figure 1. Comparison between two sampling strategies: (a) The original graph, (b) the graph sampled using *Random Walk*, and (c) the graph sampled using *Forest Fire*. The upper right corner of each subfigure shows the degree distribution. Subfigures (b) and (c) have similar degree distributions and an average degree of 2.4. However, the resulting visualizations of the samples are extremely different, indicating that the sampling strategy chosen can greatly influence the visual features present in the graph.

How can AI help graph visualization ?

Evaluating the Readability of Force Directed Graph Layouts: A Deep Learning Approach

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Yong Wang

The Hong Kong University of Science and Technology, Hong Kong, China

Abishek Puri

The Hong Kong University of Science and Technology, Hong Kong, China

Sahil Wadhwa

Blackrock, New Delhi, India

Huamin Qu

The Hong Kong University of Science and Technology, Hong Kong, China

Existing graph layout algorithms are usually not able to optimize all the aesthetic properties desired in a graph layout. To evaluate how well the desired visual features are reflected in a graph layout, many readability metrics have been proposed in the past decades. However, the calculation of these readability metrics often requires access to the node and edge coordinates and is usually computationally inefficient, especially for dense graphs. Importantly, when the node and edge coordinates are not accessible, it becomes impossible to evaluate the graph layouts quantitatively. In this paper, we present a novel deep learning-based approach to evaluate the readability of graph layouts by directly using graph images. A convolutional neural network architecture is proposed and trained on a benchmark dataset of graph images, which is composed of synthetically-generated graphs and graphs created by sampling from real large networks. Multiple representative readability metrics (including edge crossing, node spread, and group overlap) are considered in the proposed approach. We quantitatively compare our approach to traditional methods and qualitatively evaluate our approach by showing usage scenarios and visualizing convolutional layers. This work is a first step towards using deep learning based methods to quantitatively evaluate images from the visualization field.

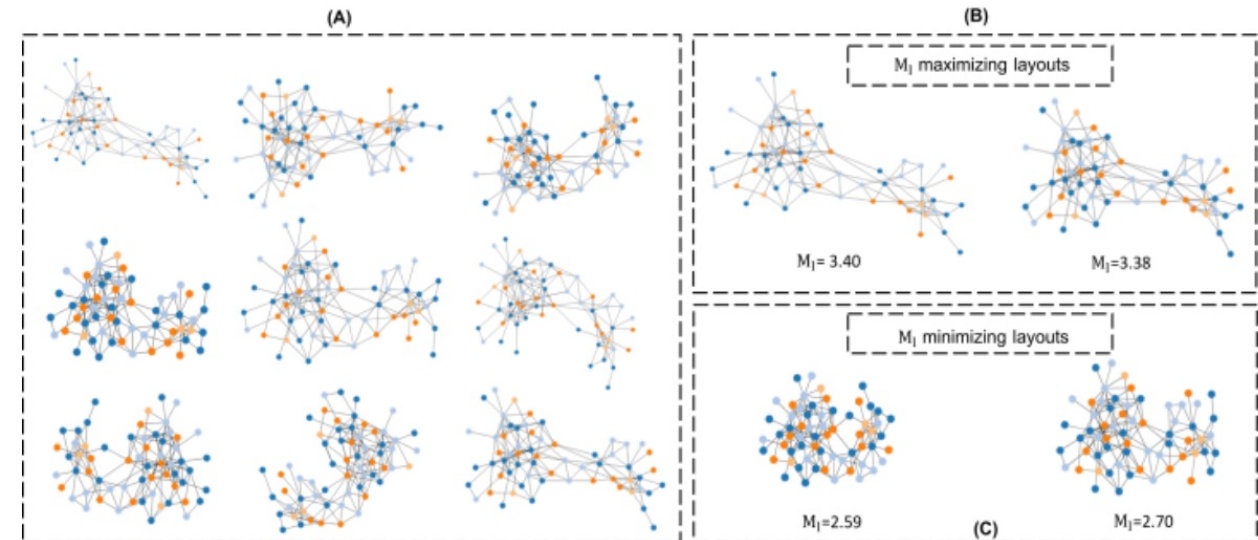


Figure 6. Given the graph layouts in (A), the proposed model can predict their M_l . The graph layouts with top-2 maximum and minimum M_l are present in (B) & (C), respectively.

DeepDrawing: A Deep Learning Approach to Graph Drawing



Yong Wang



Zhihua Jin



Qianwen Wang



Weiwei Cui



Tengfei Ma



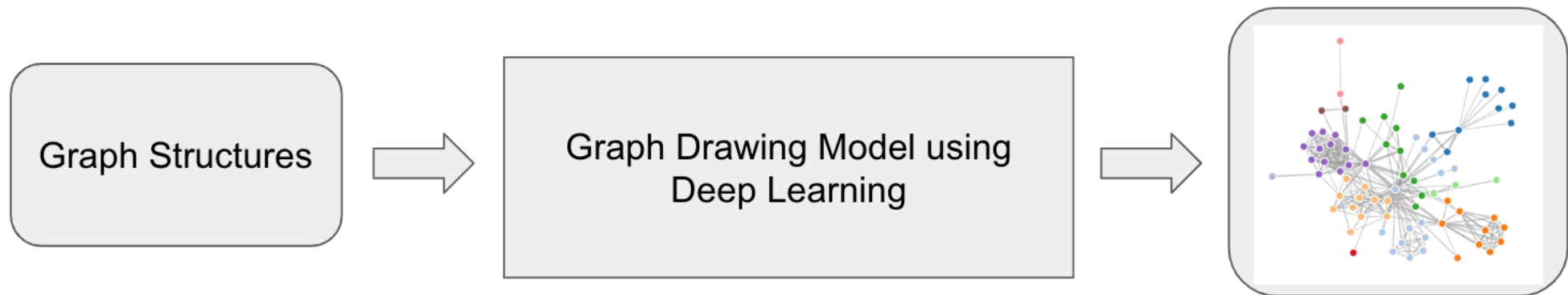
Huamin Qu

<http://yong-wang.org/proj/deepDrawing.html>

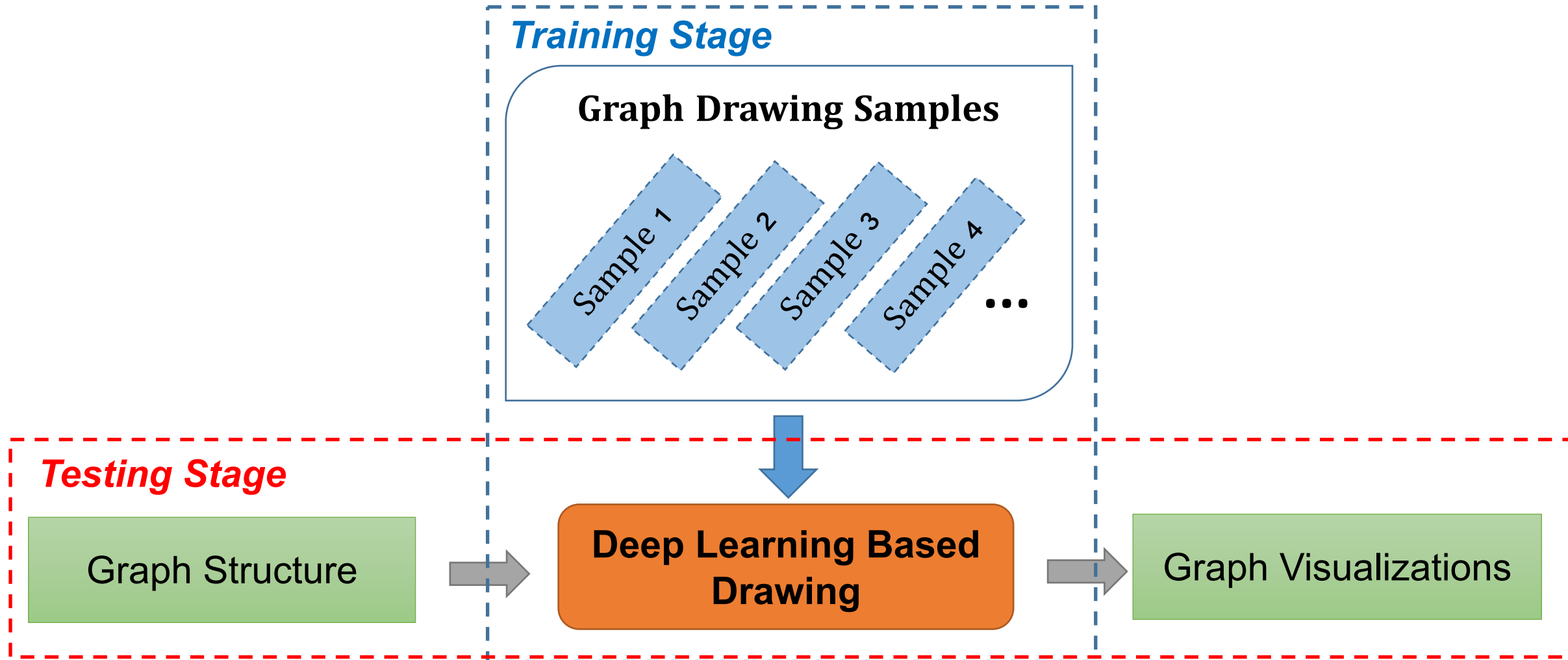
IEEE TVCG 2020 (Presented at VIS 2019)

Research Question

- Deep learning techniques have shown a powerful capability of modelling the training data and further making predictions in many applications
- Can we model graph drawing as a learning and prediction problem and further generate drawings for input graphs directly?



Overall Idea



Challenges

➤ Model Architecture

- Existing deep learning techniques are mainly applied to the Euclidean data (e.g., images, videos and texts), instead of graphs
- Recent research on Graph Neural Network mainly targets at node classification and link prediction on **a single graph**, which is much **different** from graph drawing

Challenges

- **Model Architecture**

- **Loss Function Design**

- How to evaluate whether a drawing for an input graph is "correct" or not?

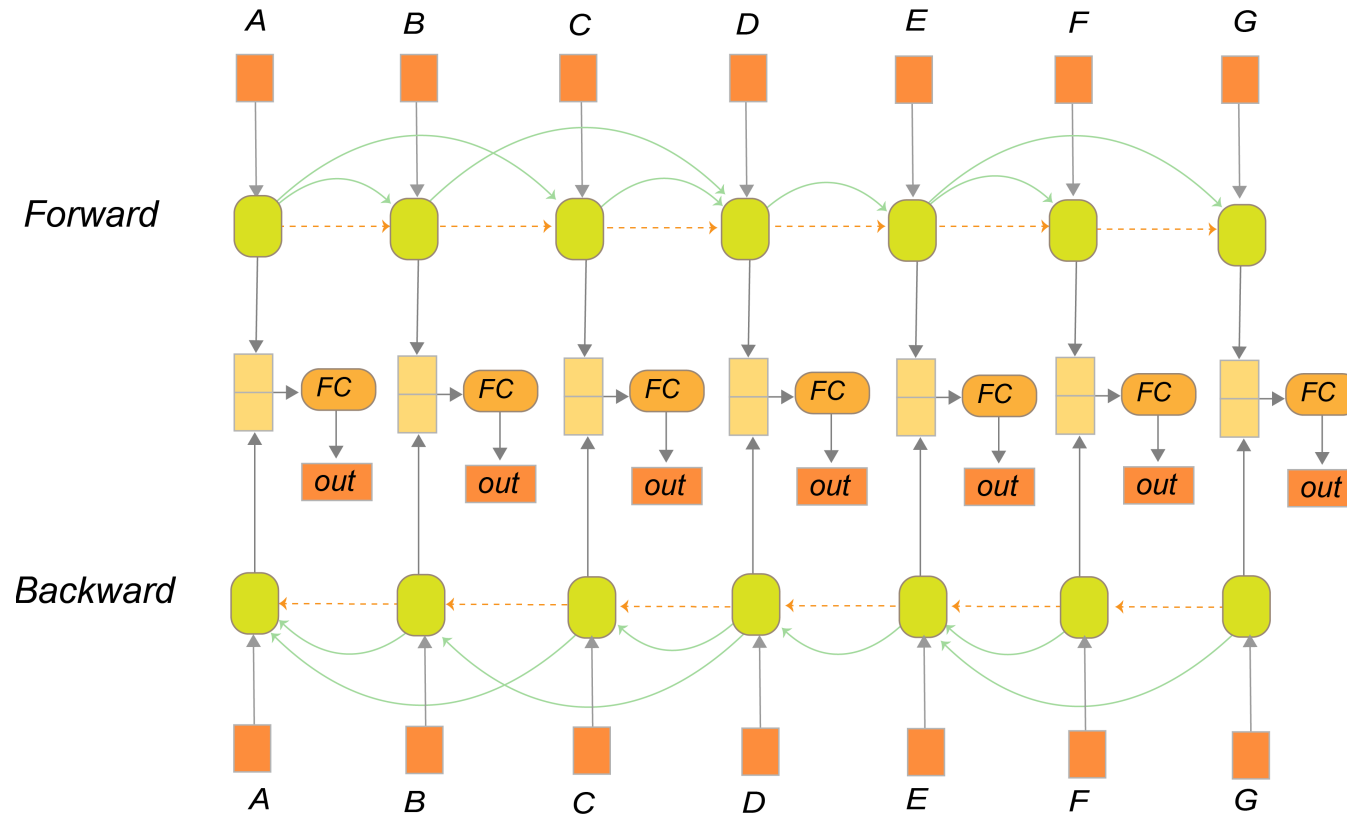
Challenges

- **Model Architecture**
- **Loss Function Design**
- **Training Datasets**
 - There are no publicly-available high-quality datasets for graph drawing

DeepDrawing

- Model Architecture
- Model Input
- Loss Function Design
- Dataset Generation

DeepDrawing – Model Architecture



We propose a bi-directional graph-LSTM based model for graph drawing.

DeepDrawing – Model Input

➤ Node Ordering

- Random ordering

The possible orderings for an input graph can be very large!

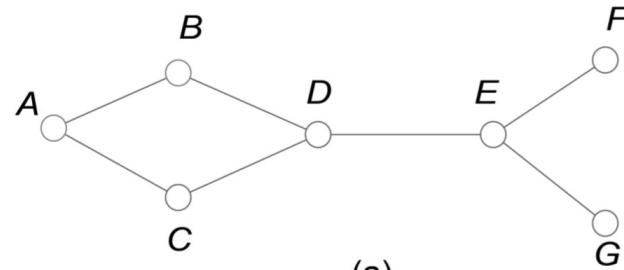
- **BFS ordering**

- Avoid exhaustively going through all possible node permutations

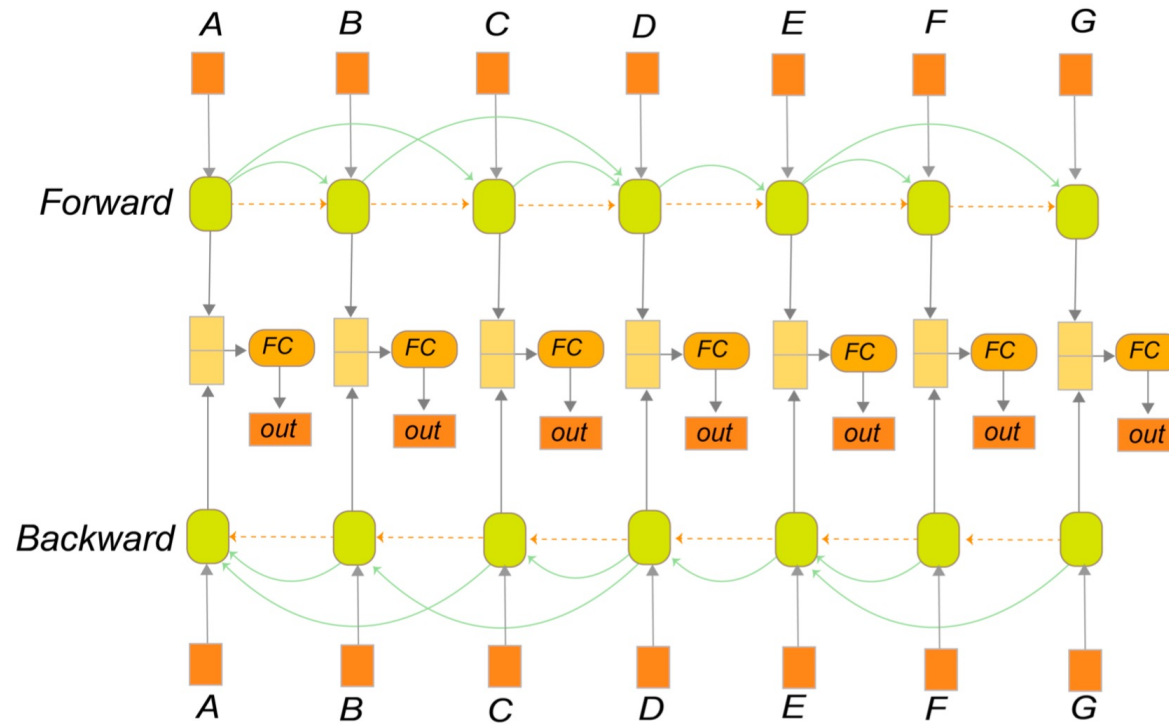
- There is an upper bound for the possible connection between the current node and its prior furthest nodes along the BFS sequence^[1]!

[1] J. You, R. Ying, X. Ren, W. L. Hamilton, and J. Leskovec. Graphrnn: a deep generative model for graphs. In *Proceedings of the 35th International Conference on Machine Learning*, 2018.

DeepDrawing – Model Input



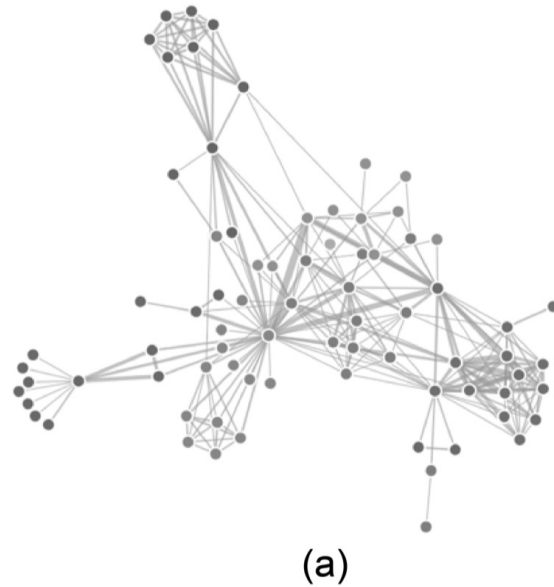
(a)



(b)

DeepDrawing – Loss Function Design

- Design Considerations
 - Make the predicted drawings as similar as possible to the drawings of ground-truth
 - The function should be **invariant to translation, rotation and scaling**



DeepDrawing – Loss Function Design

➤ Procrustes Statistic

$$R^2 = 1 - \frac{(tr(C^T \bar{C} \bar{C}^T C))^{1/2})^2}{tr(C^T C) tr(\bar{C}^T \bar{C})}$$

- It is transformation-invariant
- It is between 0 and 1
- Zero means the drawings are exactly the same; while one means they are totally different

DeepDrawing – Dataset Generation

- We generate:
 - Graph data: grid graphs, star graphs, clustered general graphs
 - Graph drawing data: grid layout, star layout, ForceAtlas2, PivotMDS
 - We manually tune the parameters of the drawing algorithms

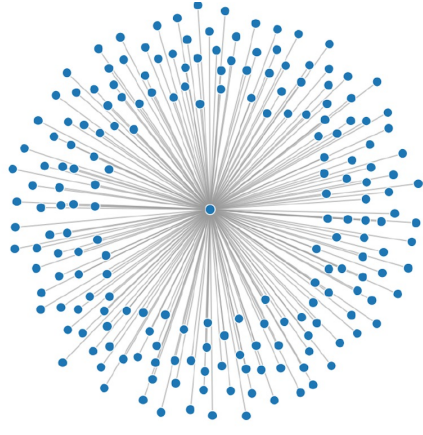
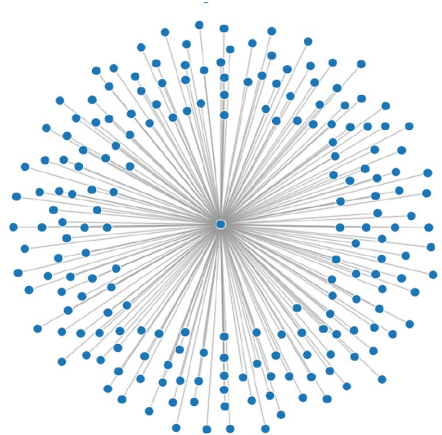
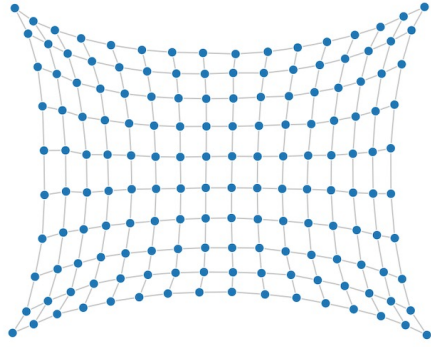
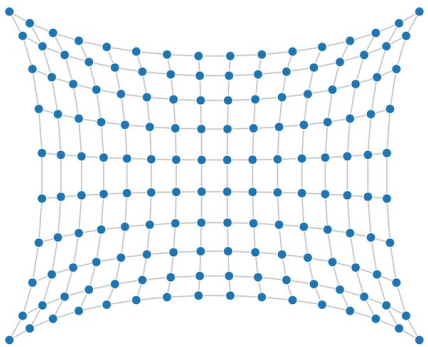
Evaluations

- We extensively evaluated the proposed approach:
 - Qualitative and quantitative evaluations
 - Comparison with the graph truth drawings and those by the baseline model (a 4-layer Bi-LSTM model)

Evaluations – Qualitative Evaluation

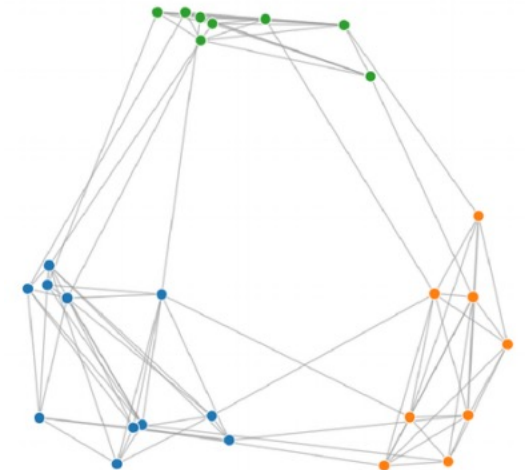
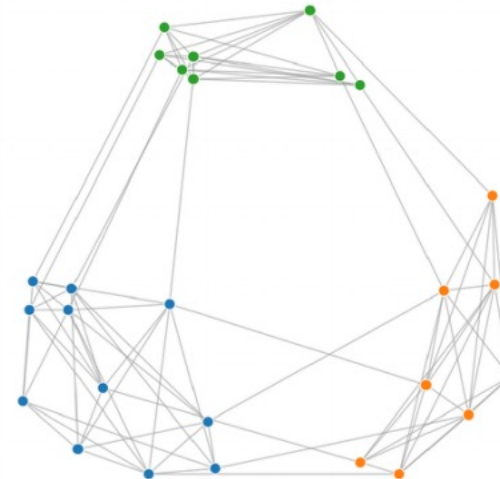
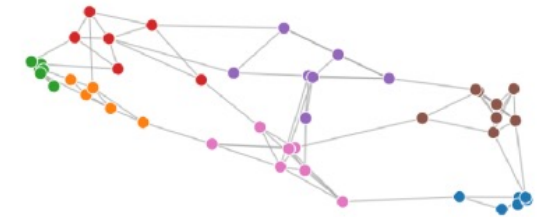
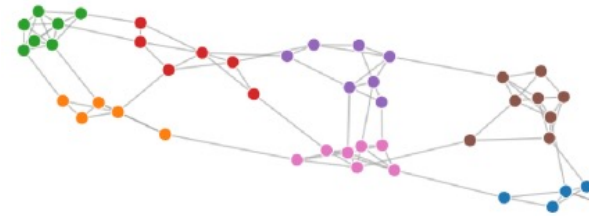
Ground-Truth

Our Approach



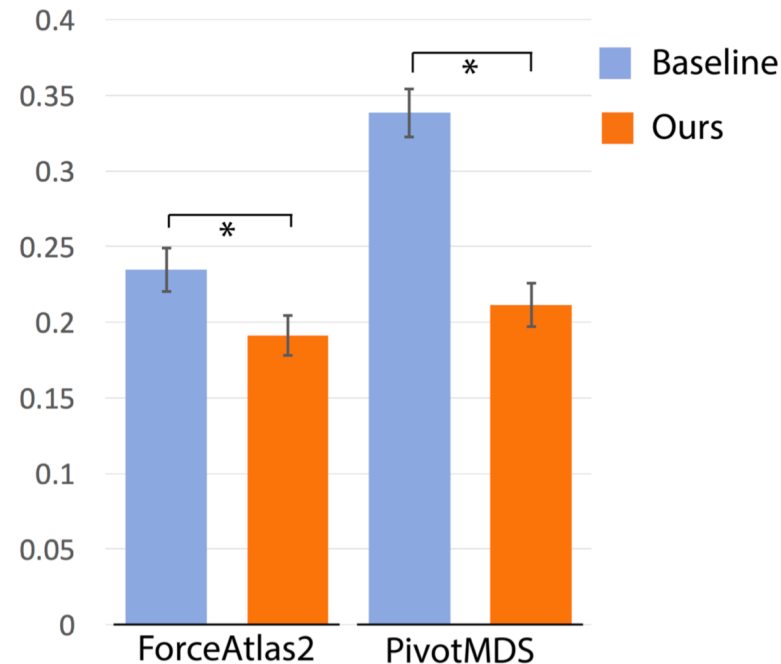
Ground-Truth

Our Approach



Evaluations – Quantitative Evaluation

- Procrustes Statistic-based similarity:
Our approach is **significantly better** than the baseline model



Limitations

- Lack Interpretability
- Our current evaluations mainly focus on **small graphs** with 20 to 50 nodes
- The performance of DeepDrawing has a dependence on the **input node ordering** and the **structure similarity** with the training graphs

Take Home Message

- We propose a graph-LSTM based approach to graph drawing and investigate its effectiveness on small graphs
- It is worth further exploration in terms of good interpretability and better prediction performance on large graphs
- More details: code, video and slides are(or will be) accessible at:
<http://yong-wang.org/proj/deepDrawing.html>

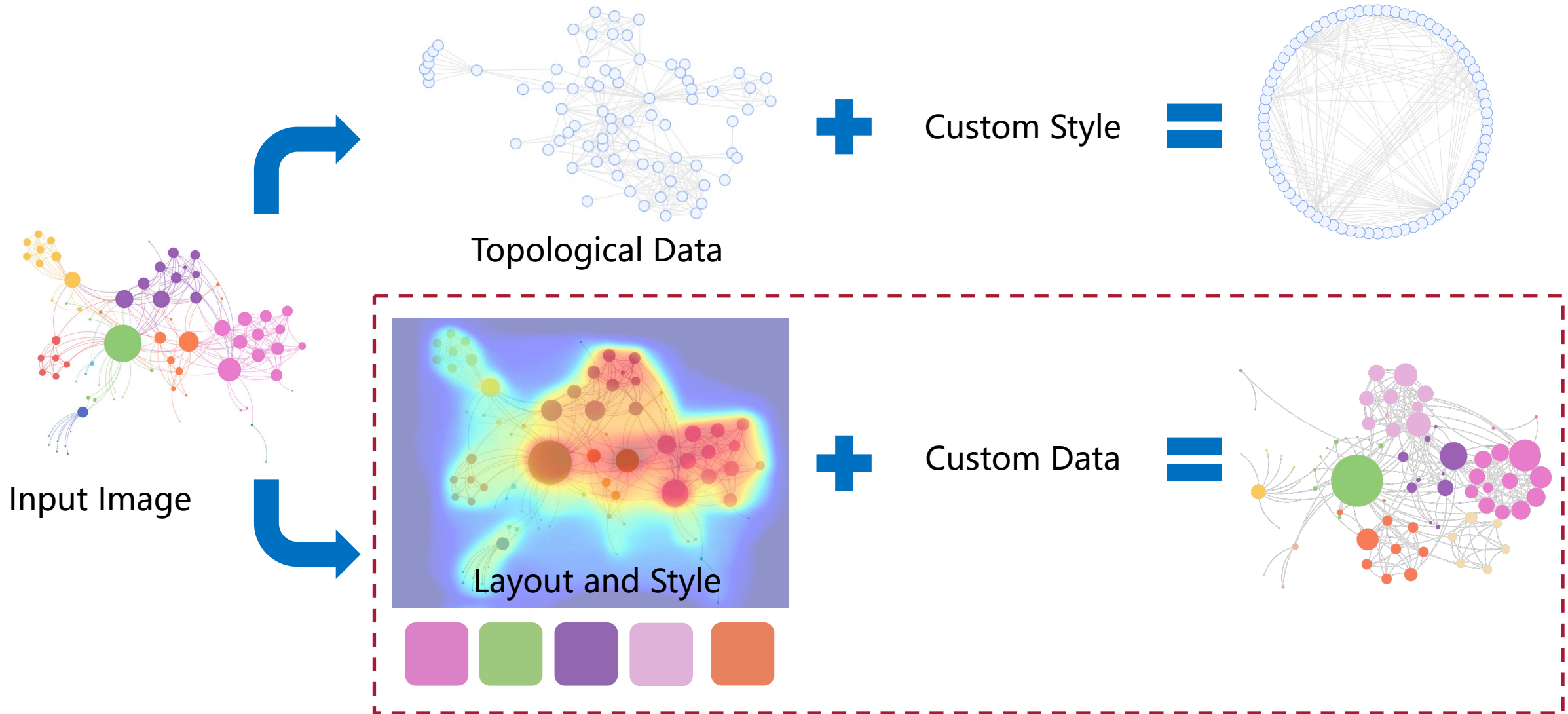
GVVST: Image-Driven Style Extraction from Graph Visualizations for Visual Style Transfer

Sicheng Song, Yipeng Zhang, Yanna Lin, Huamin Qu, Changbo Wang, and Chenhui Li

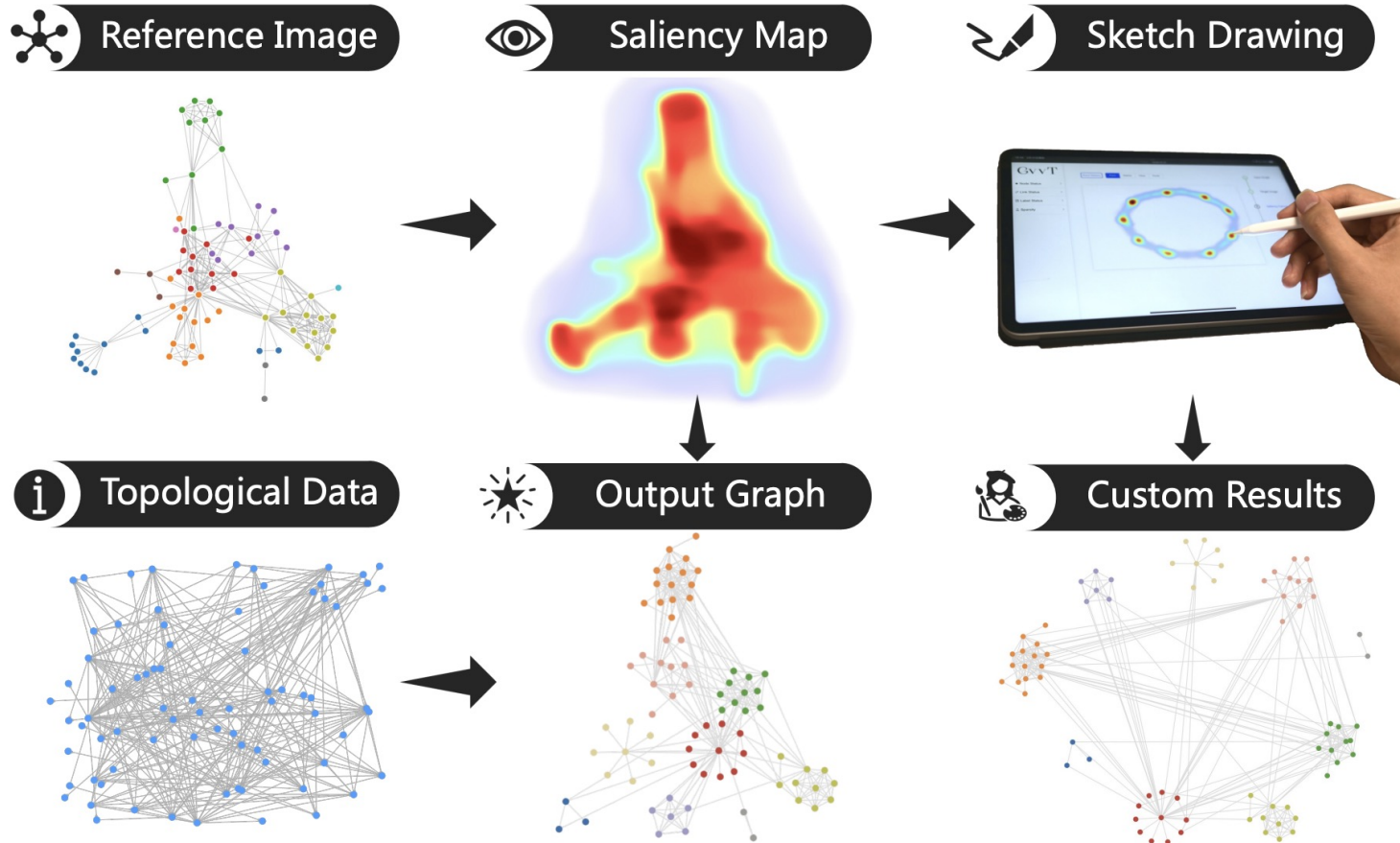
IEEE Transactions on Visualization and Computer Graphics, vol. 31, no. 9, pp. 5975-5989, Sept. 2025

To be presented at IEEE VIS'25

Problem Definition



Challenges



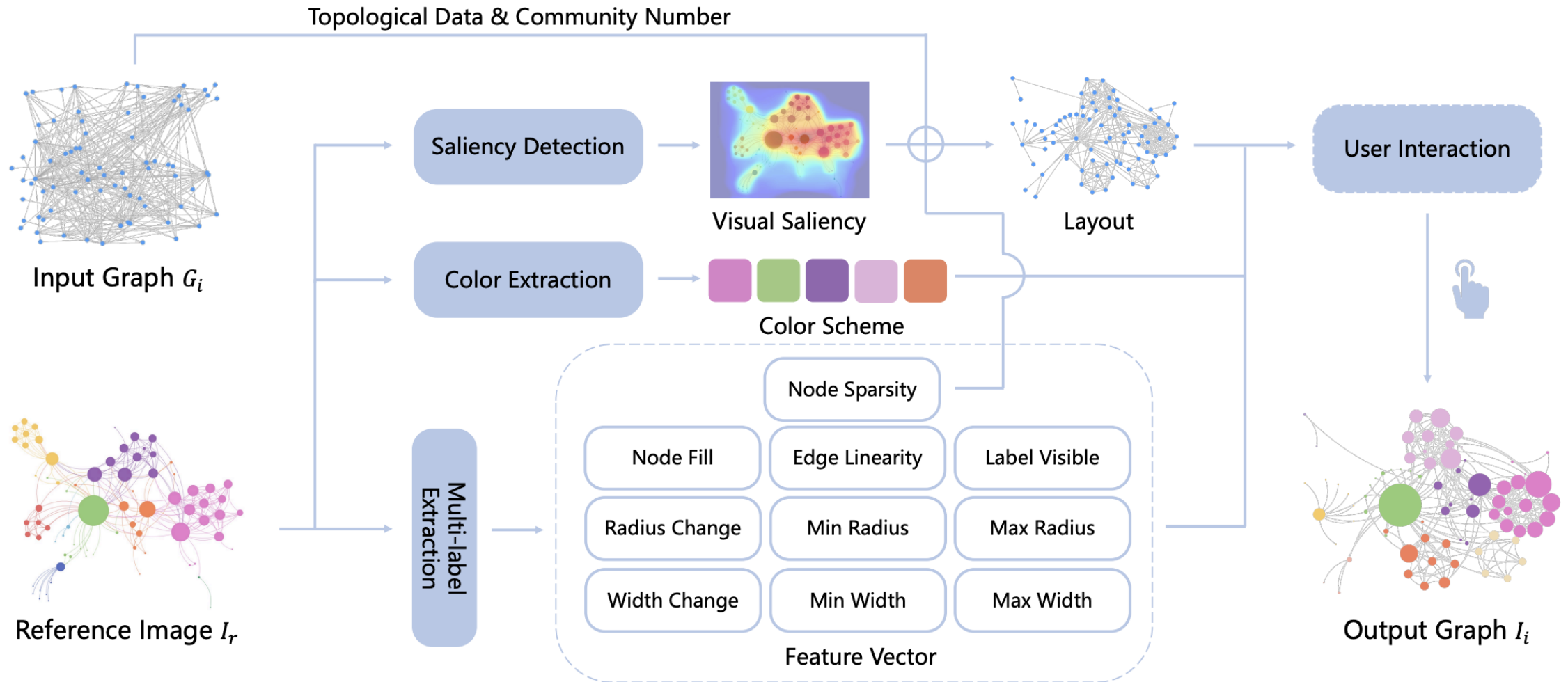
- 1 How to **define visual styles** of graph visualization?
- 2 How to make it easier for **non-professionals to draw** well-design graph visualization?
- 3 How to balance the **aesthetics and functionality** of graph visualization?

Formative Study

Style Type	Style Aspect	Total	Ratio
Global Style	Color Scheme	26	86.67%
	Layout	22	73.33%
	Sparsity	8	26.67%
Local Style	Node Radius Scale	13	43.33%
	Edge Width Scale	13	43.33%
	Node Fill	10	33.33%
	Edge Linearity	8	26.67%
	Label Status	7	23.33%
	Legend Location	3	10.00%
	Font Type	2	6.67%
	Node Shape	2	6.67%
	Font Size	1	3.33%
	Arrow Size	1	3.33%

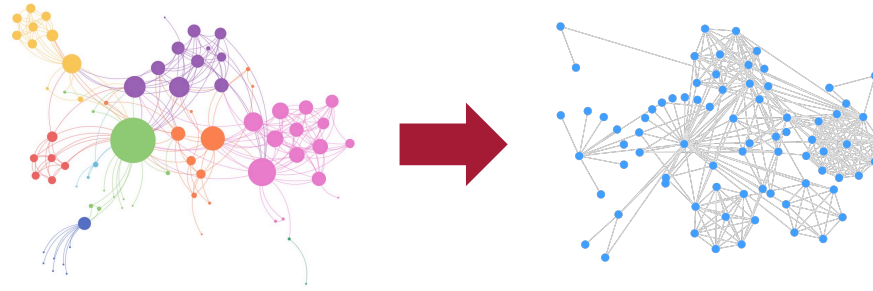
• We limited our research scope to styles that were shared by **more than 20%** of respondents, providing generally accepted guidelines for graph design.

Pipeline



Global Style Extraction

- Saliency-based graph clustering
- Node sparsity adjustment



Layout Extraction

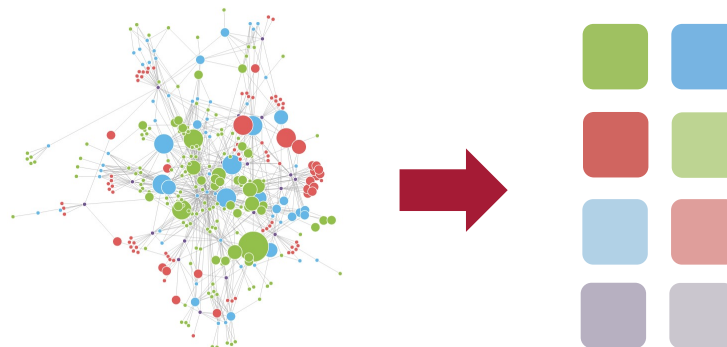
- Cluster-based clustering layout
- Force-directed layout within clusters

Aesthetics

Computational
Aesthetics

Functionality

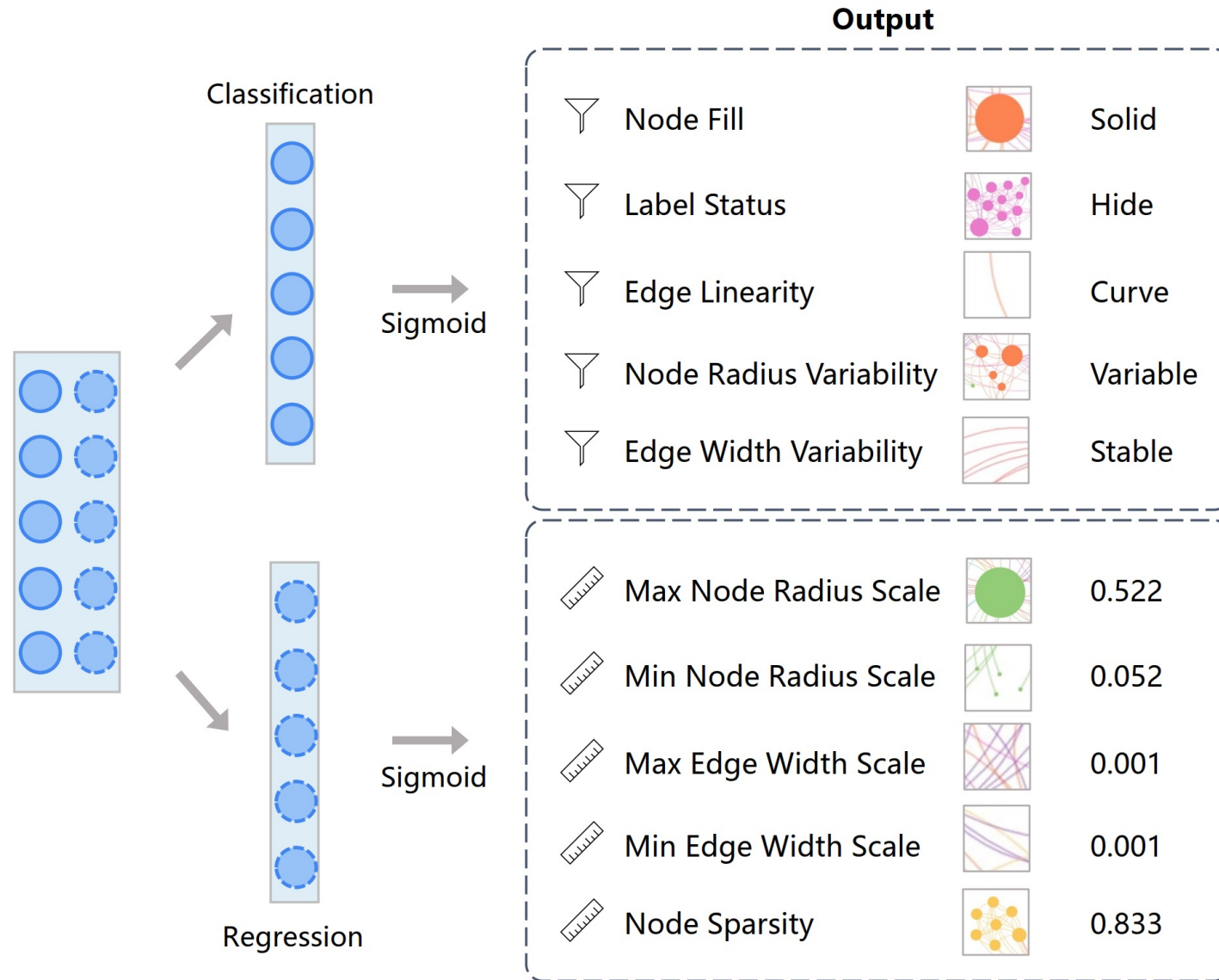
- Color coordination
- Background and highlights
- Proportional distribution



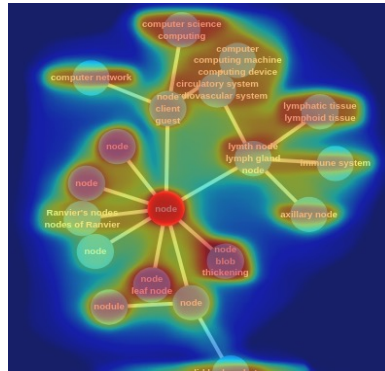
Color Scheme Extraction

- Community-based color matching
- Data adaptability

Local Style Extraction

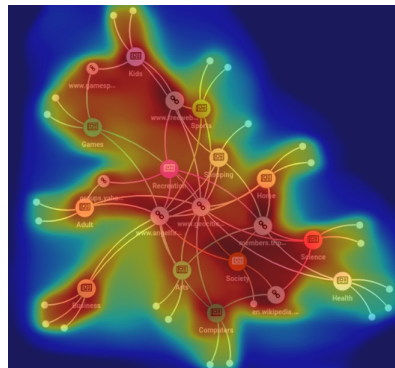
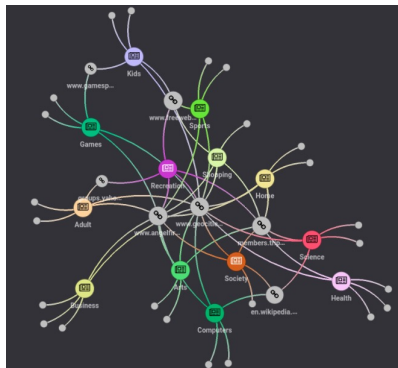
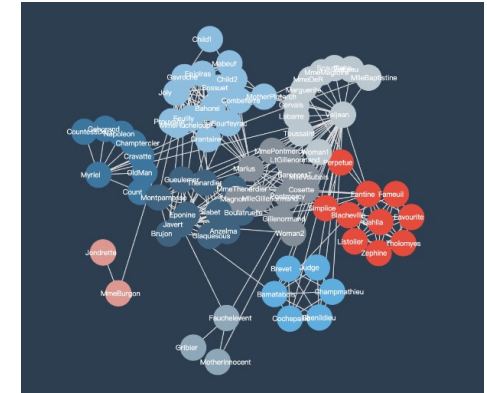


Style Transfer



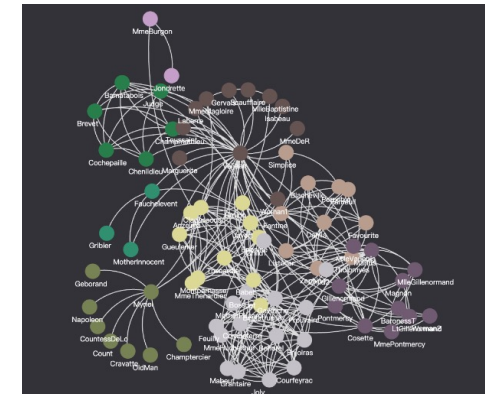
Node Fill: True
Label: True
Edge Linear.: False
Node Var.: False
Edge Var.: False

Max Node Scale: 0.476
Min Node Scale: 0.476
Max Edge Scale: 0.001
Min Edge Scale: 0.001
Node Sparsity: 0.336



Node Fill : True
Label : True
Edge Linear. : True
Node Var. : False
Edge Var. : False

Max Node Scale : 0.451
Min Node Scale : 0.069
Max Edge Scale : 0.001
Min Edge Scale : 0.001
Node Sparsity : 0.639



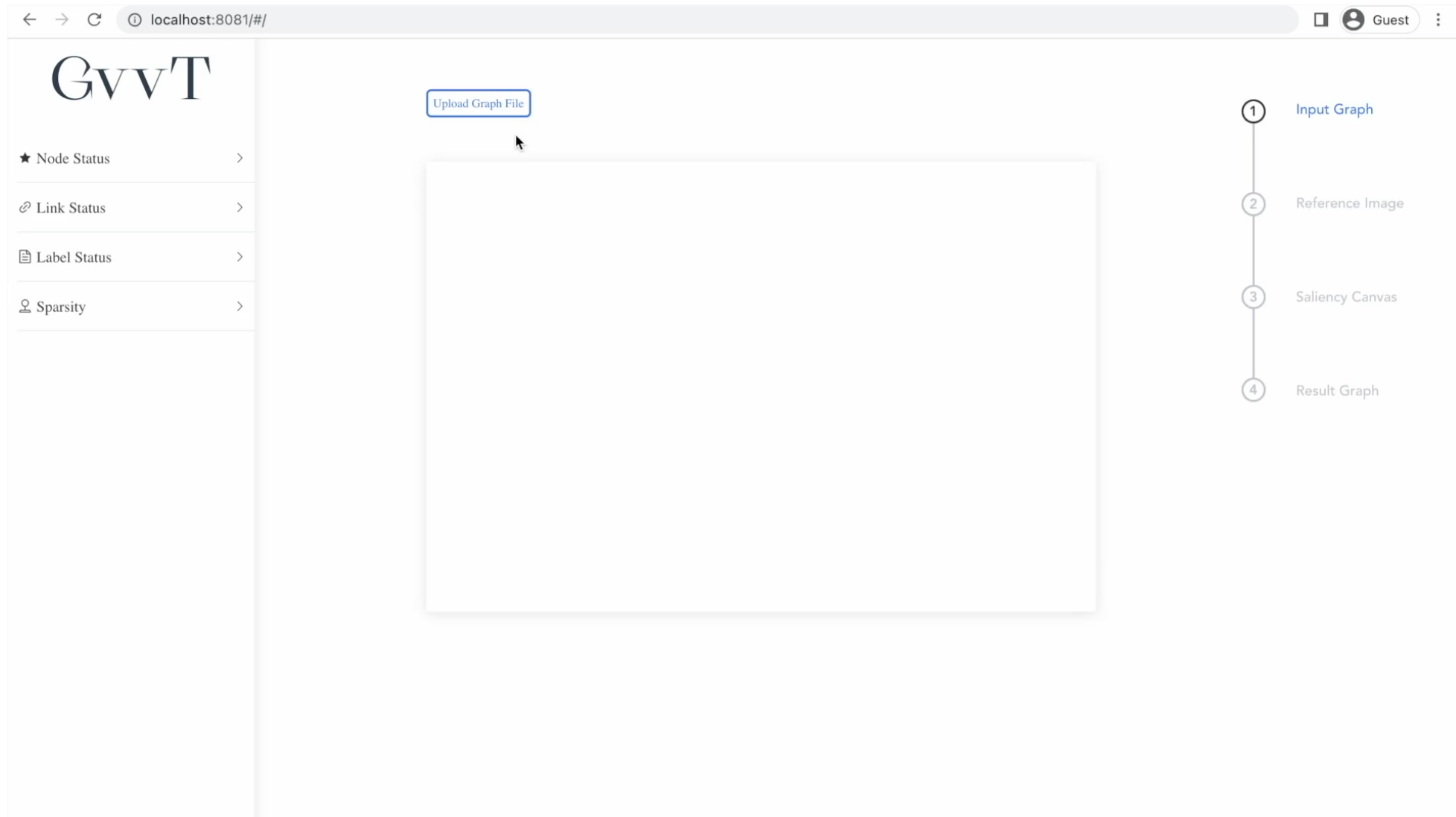
Reference

Global Style

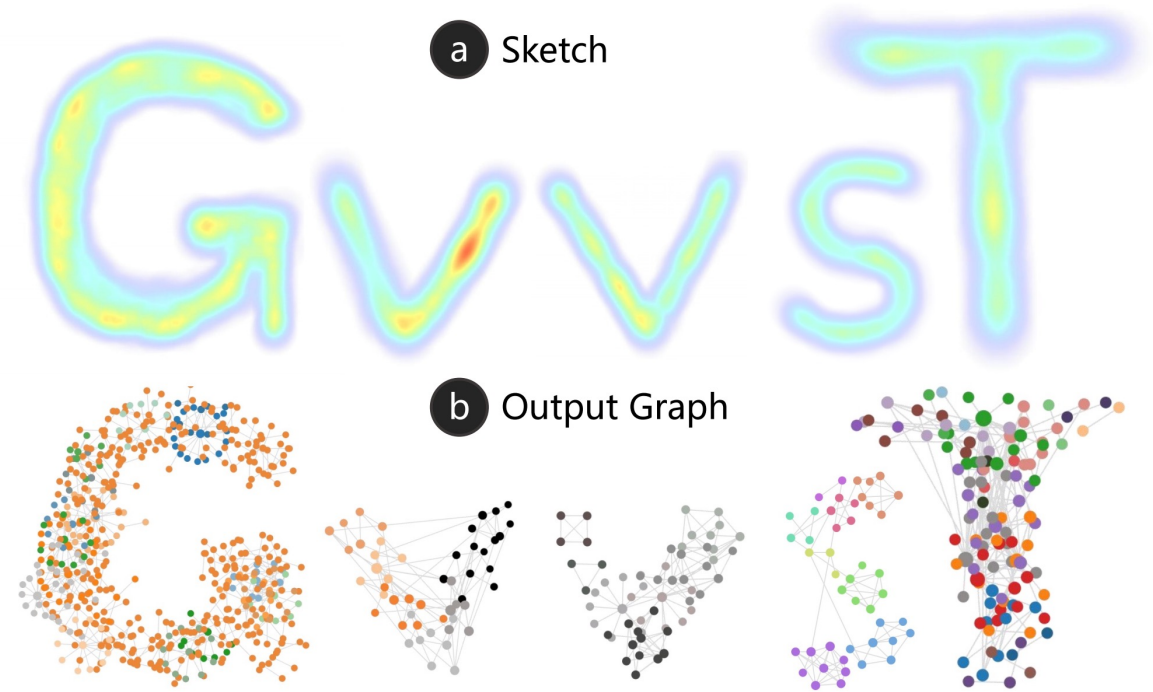
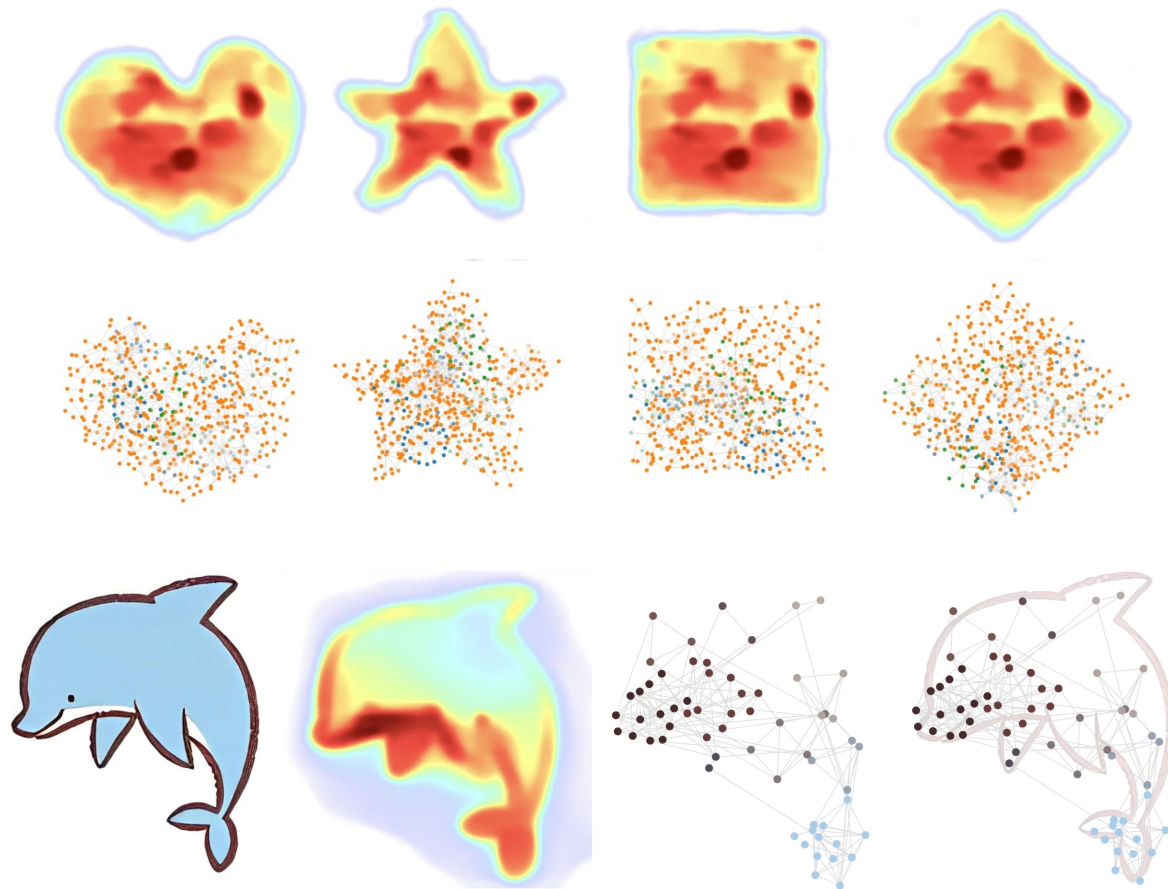
Local Style

Mapping

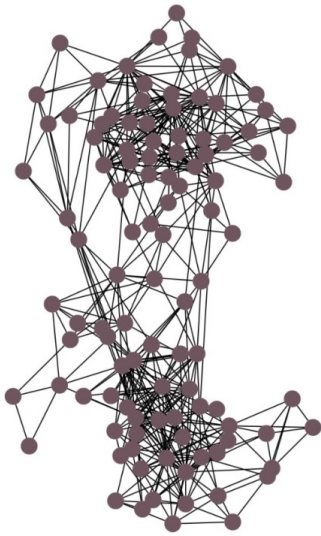
Application



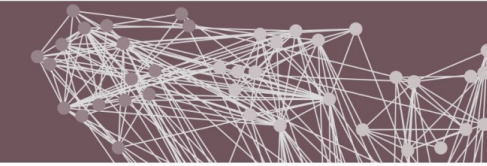
Application



Application



Political
Books

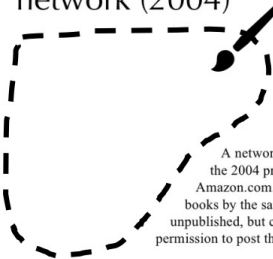


Political
Books



(a) Input Graph

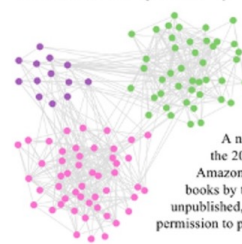
Polbooks Dataset:
Political books
network (2004)



A network of books about US politics published around the time of the 2004 presidential election and sold by the online bookseller Amazon.com. Edges between books represent frequent copurchasing of books by the same buyers. The network was compiled by V. Krebs and is unpublished, but can found on Krebs' web site. Thanks to Valdis Krebs for permission to post these data on this web site.

(b) Drawn Irregular Area

Polbooks Dataset:
Political books
network (2004)



A network of books about US politics published around the time of the 2004 presidential election and sold by the online bookseller Amazon.com. Edges between books represent frequent copurchasing of books by the same buyers. The network was compiled by V. Krebs and is unpublished, but can found on Krebs' web site. Thanks to Valdis Krebs for permission to post these data on this web site.

(c) Result

How can graph visualization be
more interesting ?

Data Storytelling



Hans Rosling's 200 Countries, 200 Years, 4 Minutes - BBC Four

10M views • 13 years ago



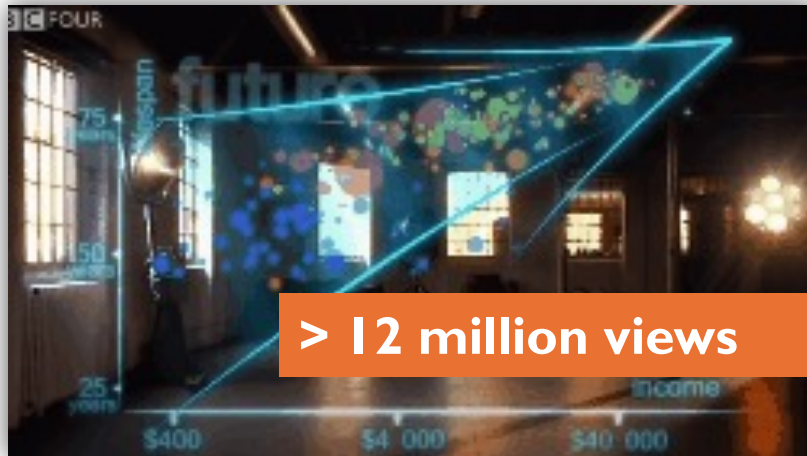
#bbc All our TV channels and S4C are available to watch live through BBC iPlay

CC



3 moments The World 200 Years Ago in 1810 | World in 1948 | C

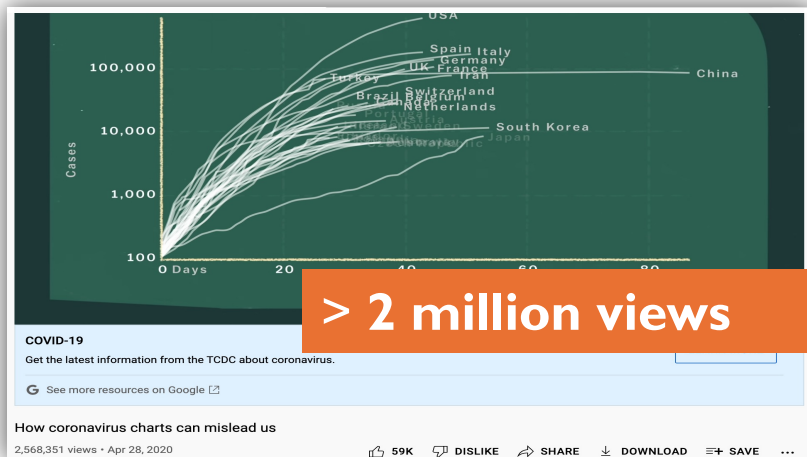
Data Storytelling is Everywhere



Economics @BBC News



Public health communication @WHO



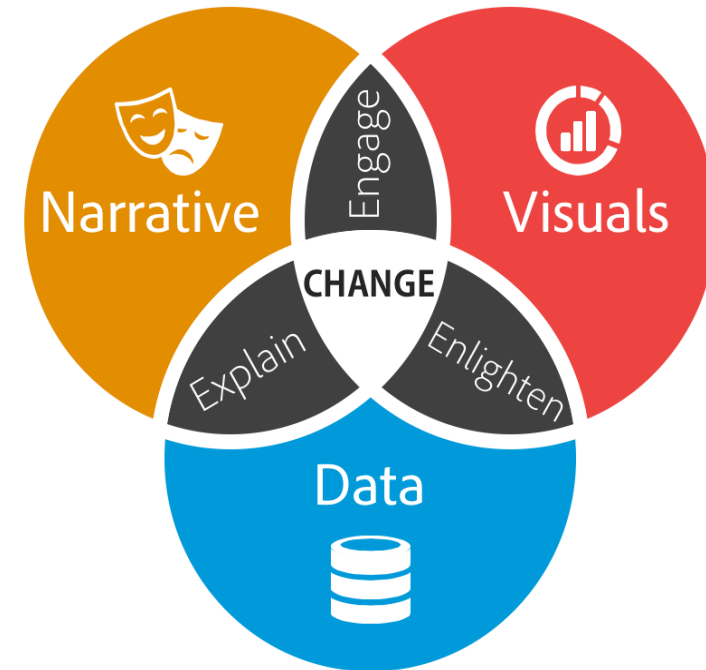
Covid19, Public Health @Vox



Wars @Neil Halloran

Definition of Data Storytelling

Data storytelling leverages the **art of visual and narratives** to make data communication **understandable, engaging, and enlighten**, ultimately driving changes.



Effective data storytelling
@Brent Dykes

NetworkNarratives: Data Tours for Visual Network Exploration and Analysis

Wenchao Li¹, Sarah Schöttler², James Scott-Brown², Yun Wang³,
Siming Chen⁴, Huamin Qu¹, Benjamin Bach²

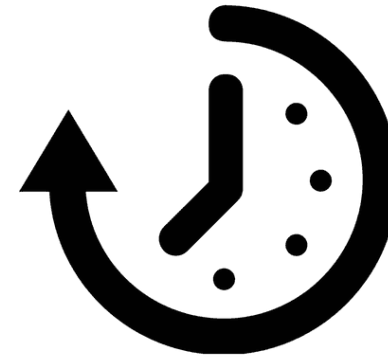
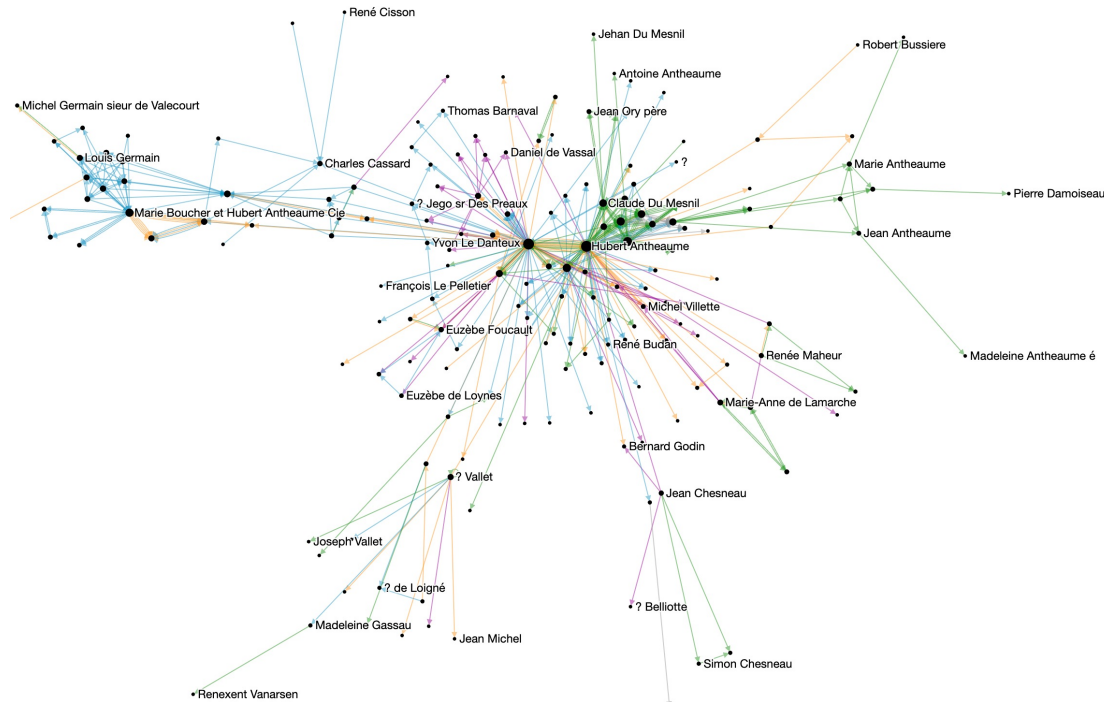


CHI23

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April 23-28, 2023
reCHInnecting



Network Exploration



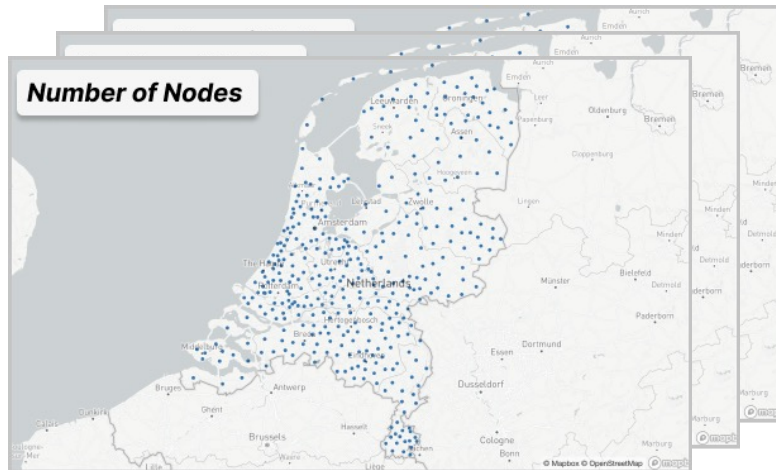
Time-consuming



Challenging

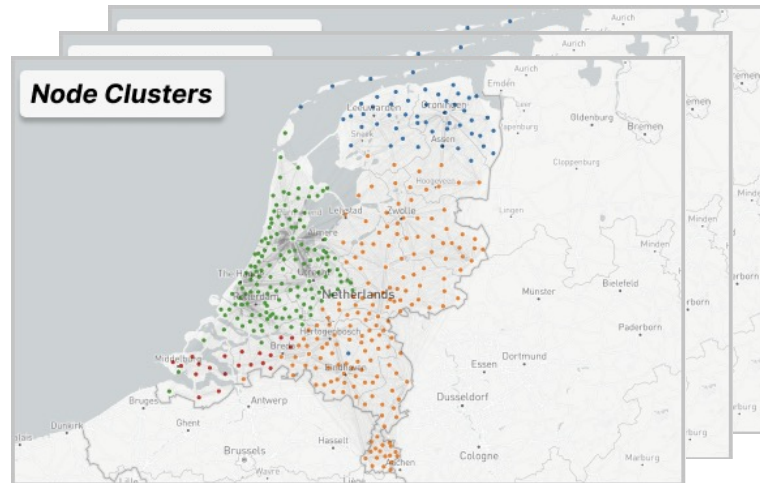
Semi-automatic Data Tours

Network overview



This network has 388 cities.

Community exploration



This network can be divided into 4 clusters.

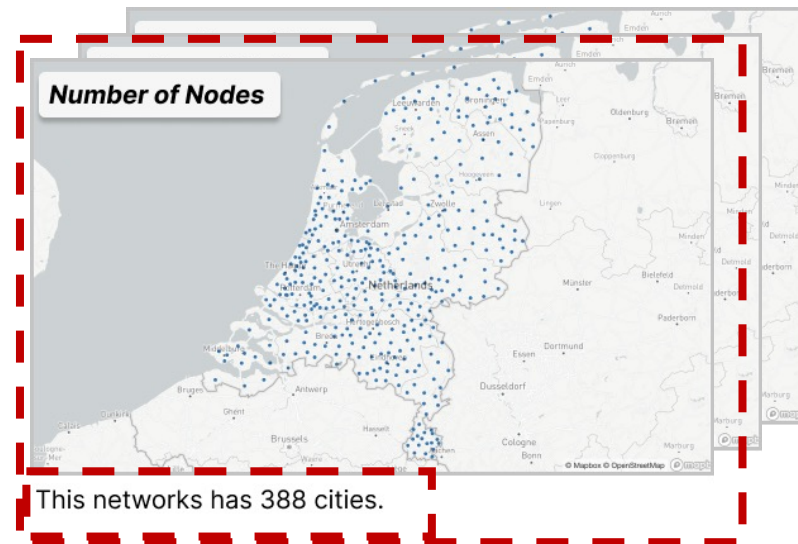
Ego-network analysis



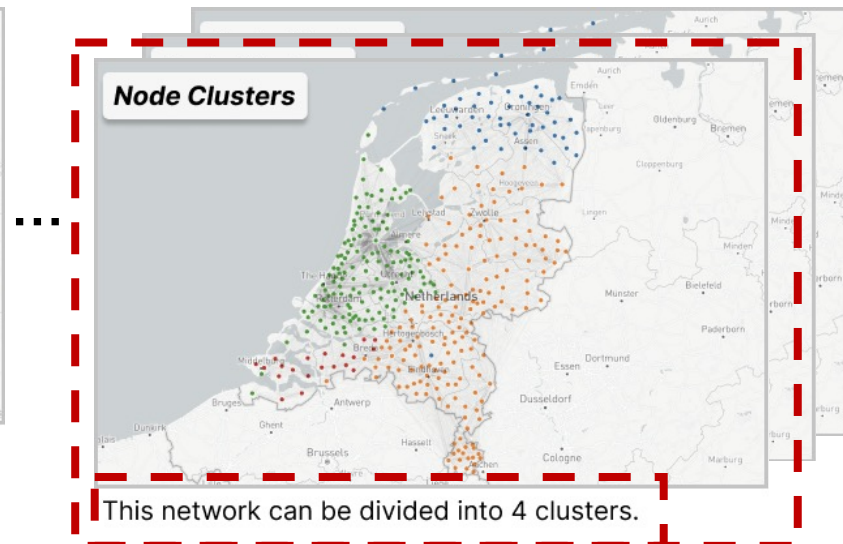
The city (Amsterdam) has 129,100 incoming flow weight and 326,200 outgoing flow weight.

Slides in a Data Tour

Network overview



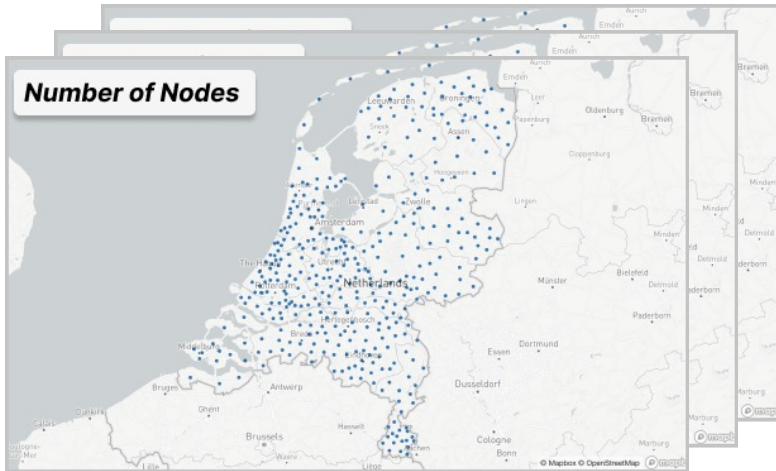
Community exploration



Each **slide** in a tour shows a **piece of information (fact)**

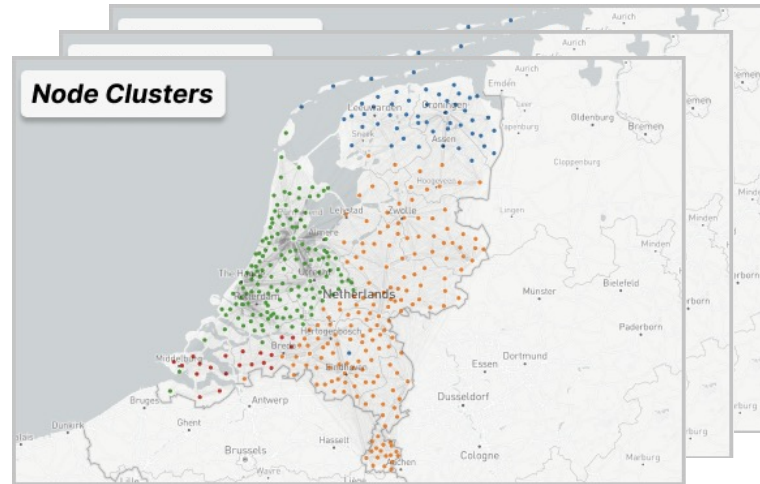
Main Characteristics of Data Tours

Network overview



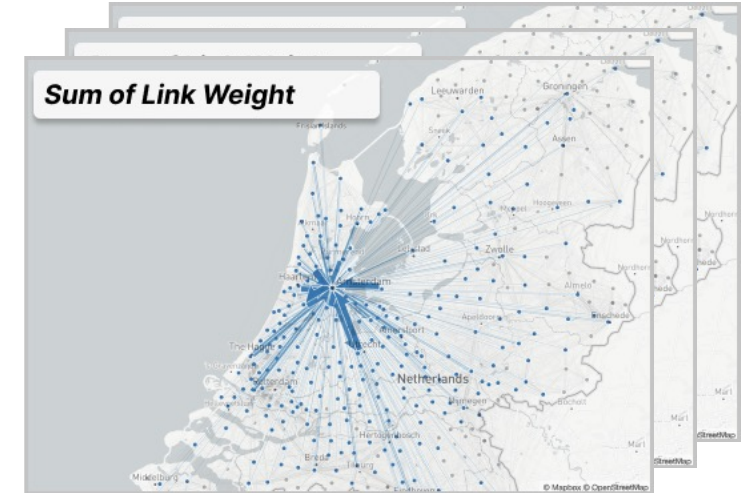
This network has 388 cities.

Community exploration



This network can be divided into 4 clusters.

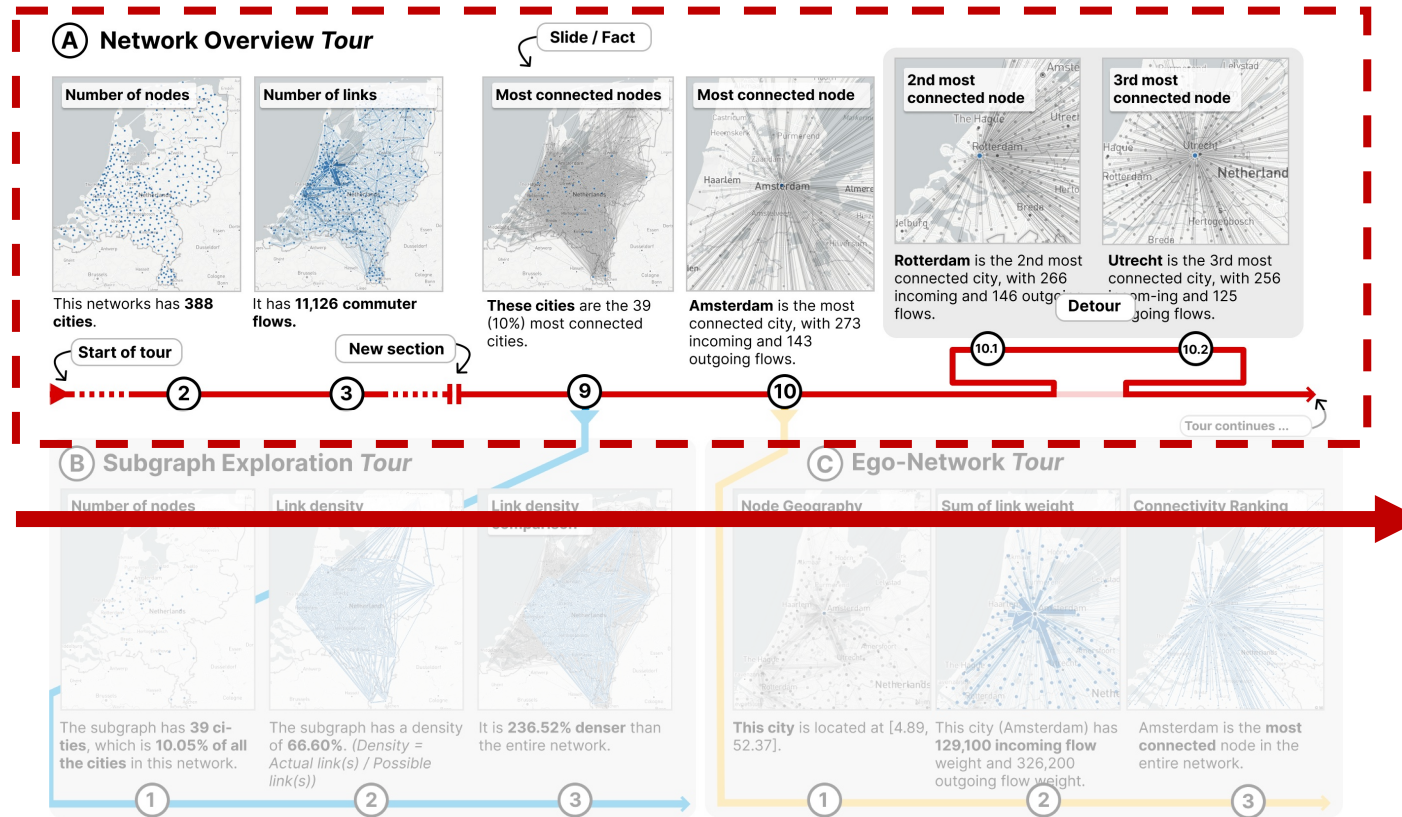
Ego-network analysis



The city (Amsterdam) has 129,100 incoming flow weight and 326,200 outgoing flow weight.

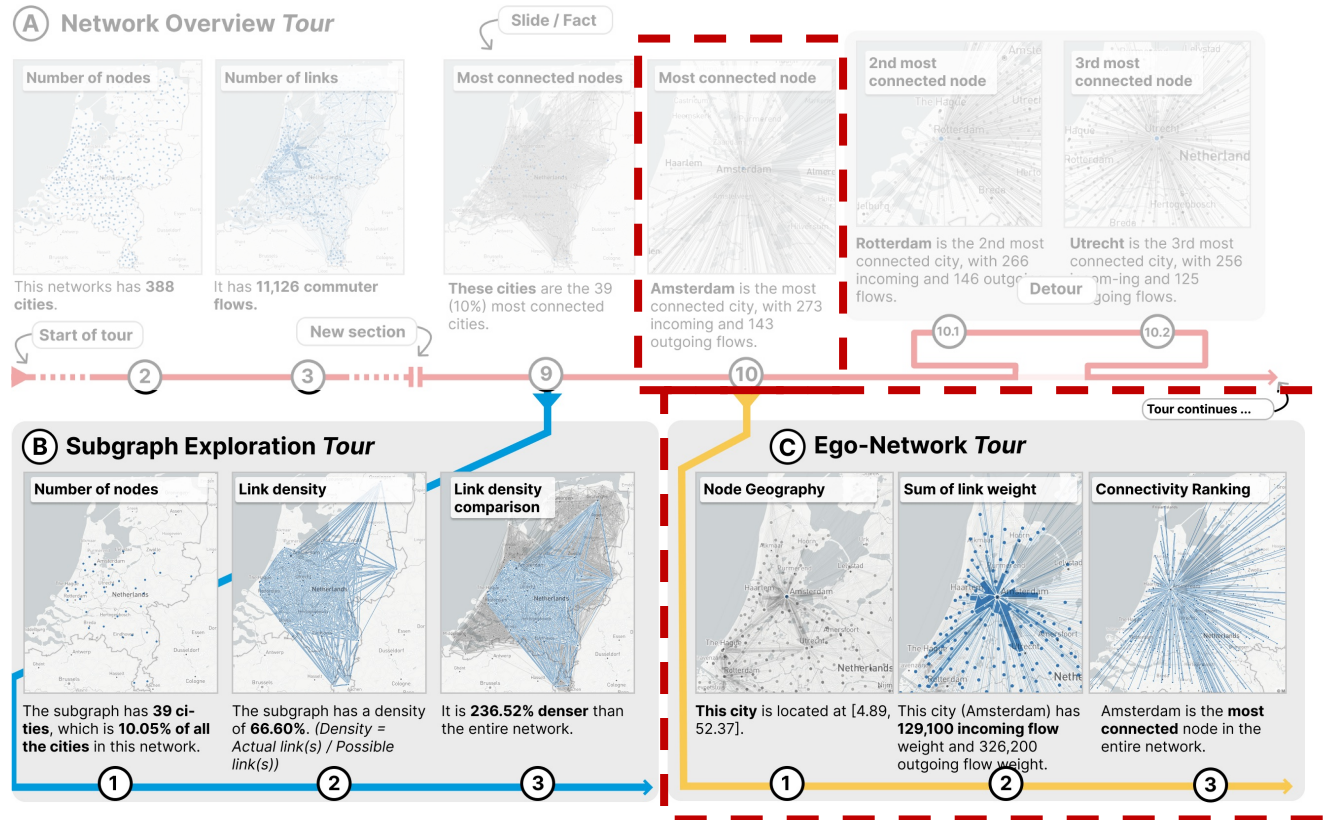
1. Unlike guidance and recommender systems for visual analytics, our approach is **goal-driven**.

Main Characteristics of Data Tours



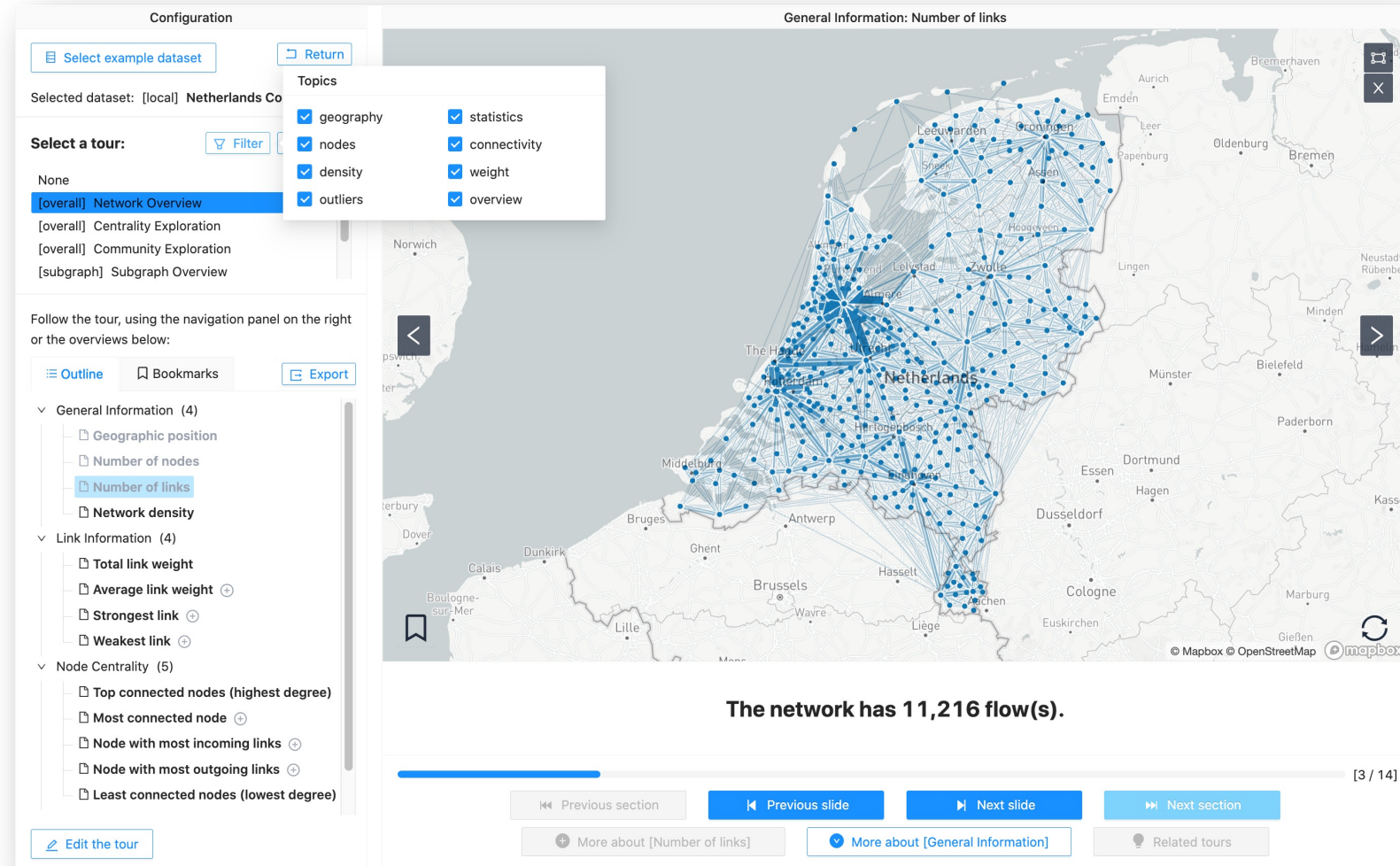
2. Tours are primarily **sequential**.

Main Characteristics of Data Tours



3. The implemented 10 complementary example data tours can be **linked** so an analyst can pivot between them

NetworkNarratives User Interface

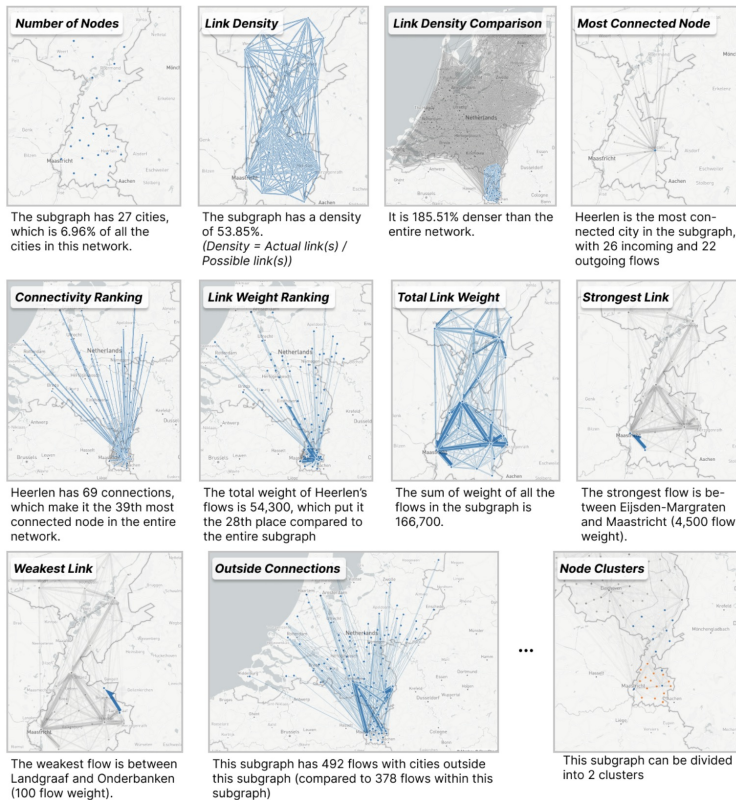


Please visit: <https://networknarratives.github.io>



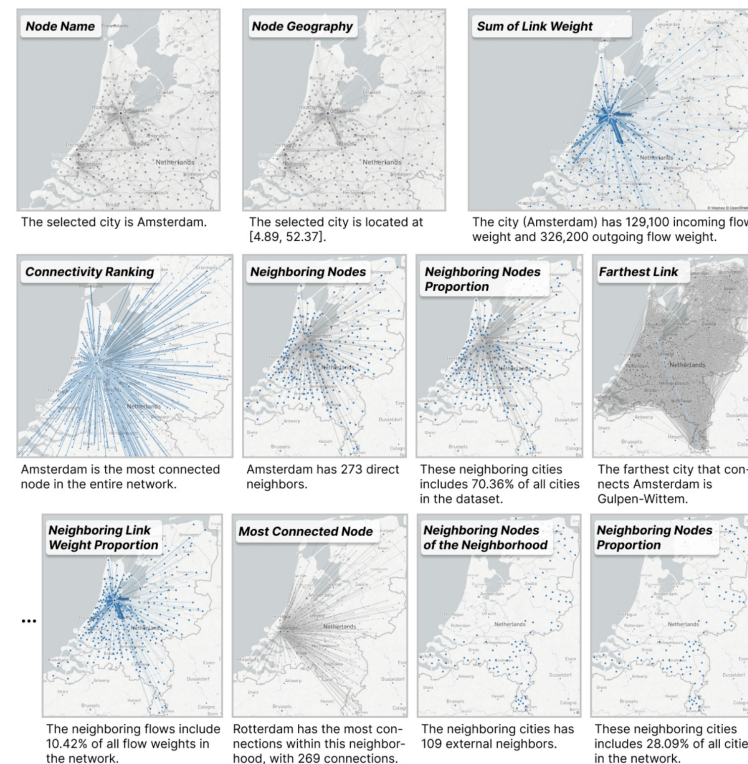
Subgraph Overview

Subgraph Overview is similar to Network Overview but focuses on a specific subgraph. It shows the subgraph's size and the percentage of the network's nodes it comprises, important nodes, density, and important links to the rest of the network. After selecting the templates, a user is asked to select a subgraph using a lasso selection tool.



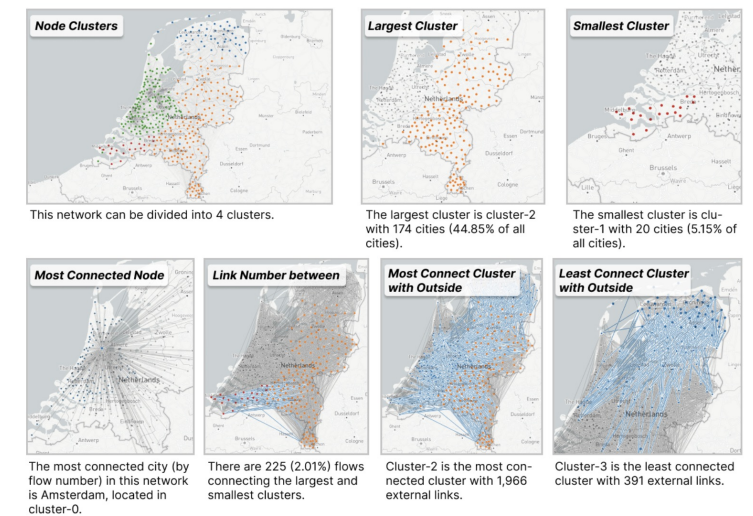
Ego-Network Exploration

This data tour explores the network around a selected node and its neighbors. The tour starts with the selected node and its position within the entire network. The template then explores the node's direct neighborhood (nodes, links, strong connections), then their mutual connections, and finally, its neighbors' neighbors. Possible Paths explores a set of possible paths between two selected nodes. The tour reports on path length, combined weights along each path, and the minimum link weight within each path. This data tour was motivated by Archaeologist's desire to explore historical travel costs between cities.



Centrality Exploration

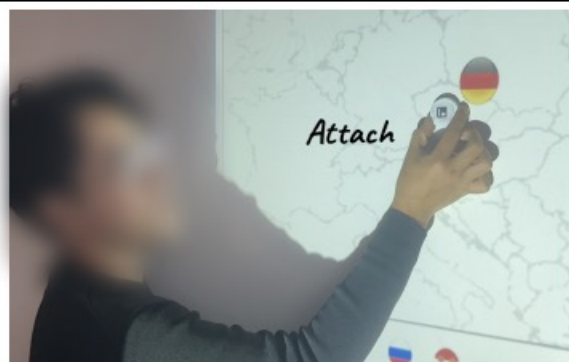
This data tour explores nodes based on different centrality measures (e.g., degree or betweenness). For example, we compute the node with the Highest centrality for both Betweenness centrality and Closeness centrality. Possible extensions include the comparison of several centrality measures. Subgraph Comparison compares two specified subsets of nodes and links (e.g., regions, subgraphs). Selecting this template prompts the user to select two sets of nodes. The tour first mentions the Number of nodes and the Number of links for each subgraph, then details important nodes such as the Most connected node in each, and finally shows links between the two subgraphs (e.g., Number of links, their Total link weight, and the Strongest link among them).



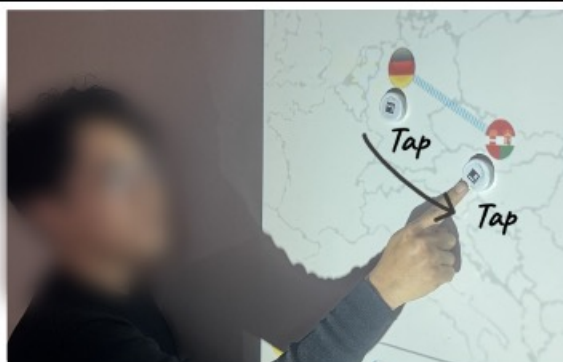
Discussions

Data tours are **complementary** to free-form tools

Cond.	Advantages	Disadvantages
TOURS	Orients users with a narrative. Automatically provides facts. Can inspire deepened exploration. May lead to additional discoveries. Easy navigation. Saves time. Helps learn about analysis.	Can limit thinking and feel passive. Explanations need to be chosen carefully. Supports a rich set of views.
FREE-FORM	Provides greater flexibility for exploration.	Harder to obtain deep insights or spot patterns with low prominence. Requires more time and effort to interact. Requires users to know where to look/have an exploration strategy.



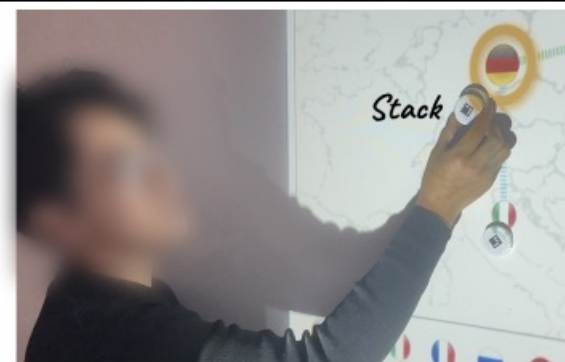
 Show/Hide Node



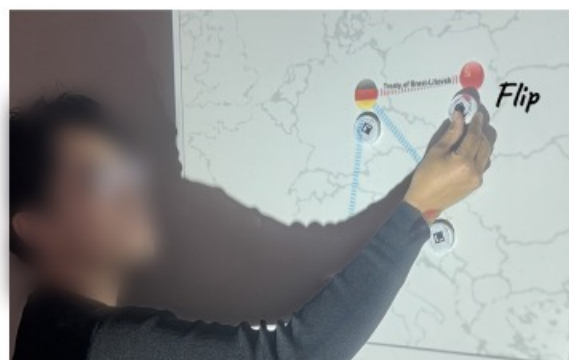
 Show/Hide Link



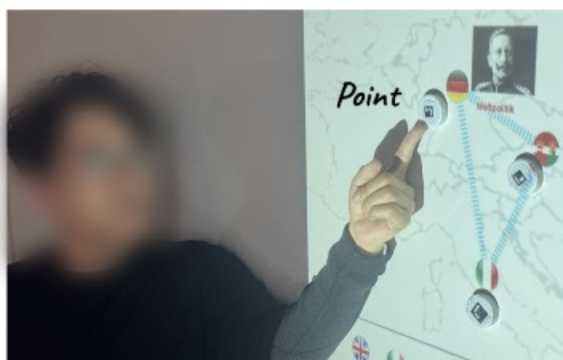
 Scale Node



 Highlight Node



 Change Node State



 Show Annotation



 Group/Ungroup Node



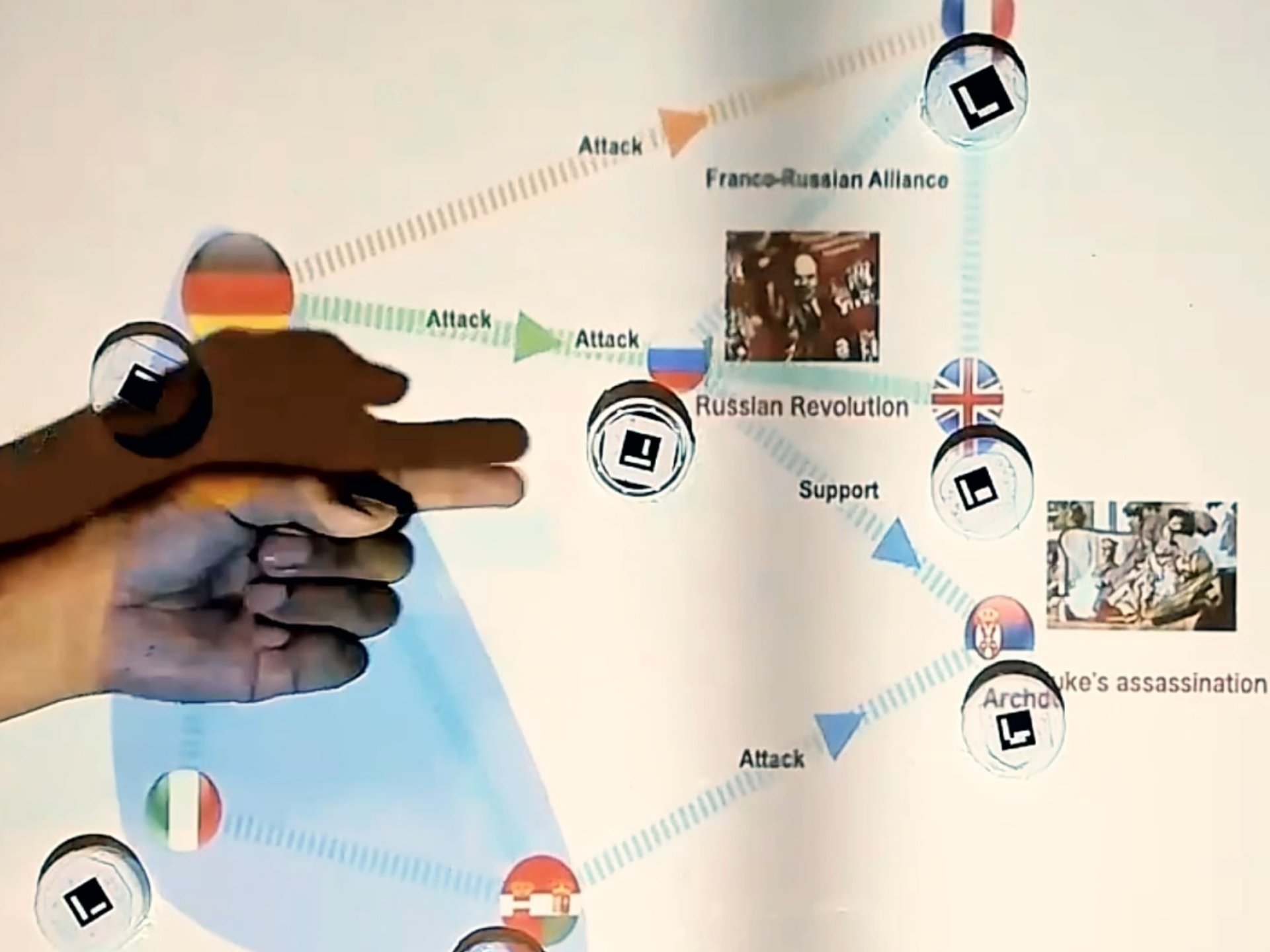
TangibleNet

Synchronous Network Data Storytelling through Tangible Interactions in Augmented Reality

Kentaro Takahira, Wong Kam-Kwai, Leni Yang, Xian Xu
Takanori Fujiwara and Huamin Qu



CHI 2025
Yokohama, Japan



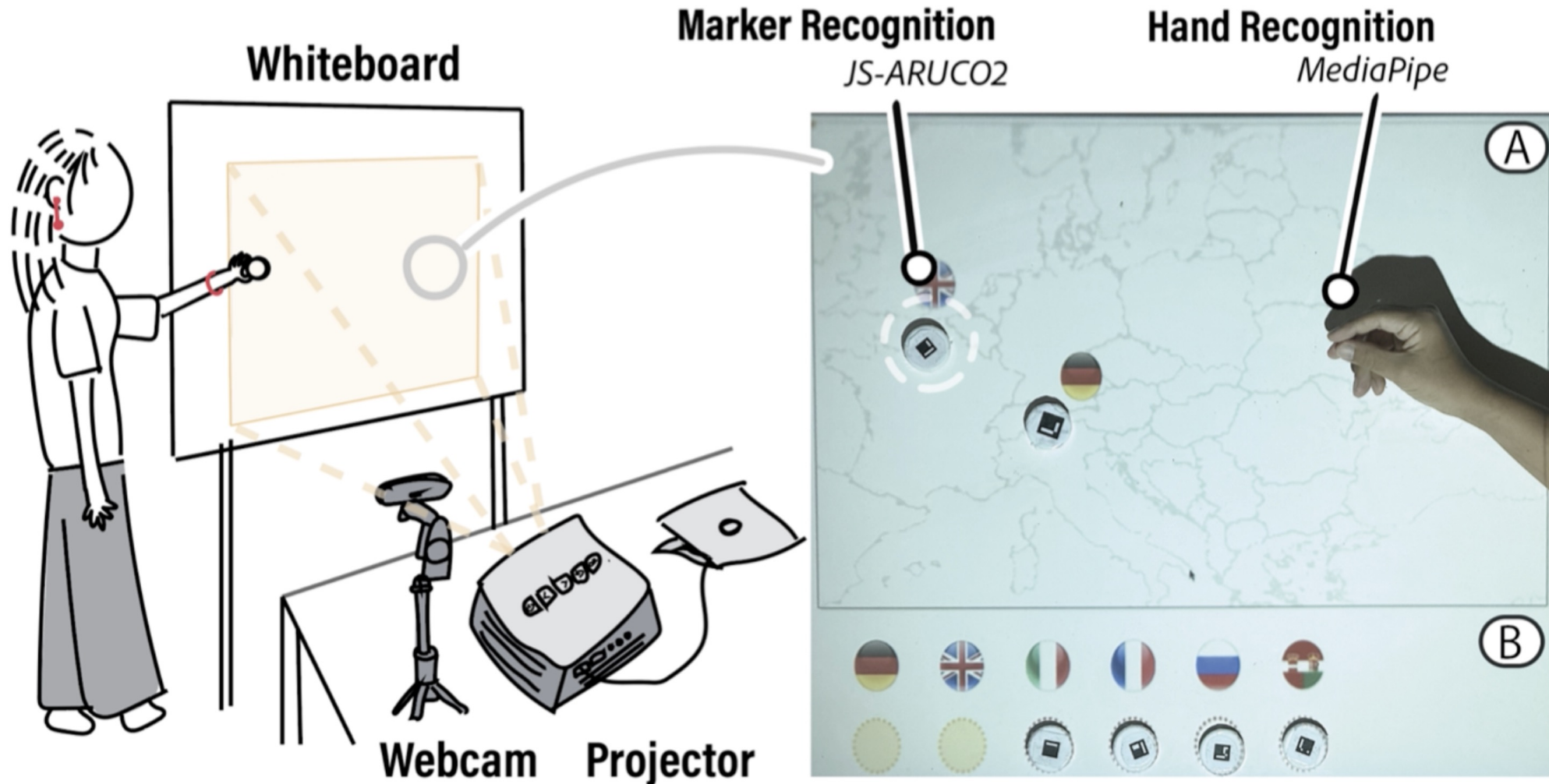


Need for **Interactive Live Data Storytelling** System for **Node-link Diagram**

By interacting with the node-link diagram **improvisationally**, the presenter can deliver a more **personalized** and **engaging** experience for the audience.

Settings of TangibleNet

TangibleNet is a web-based application utilizing a webcam, a projector, magnets, and a whiteboard

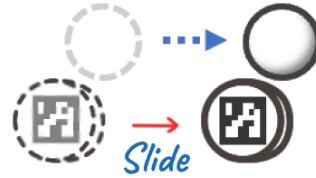


Supported Interactions



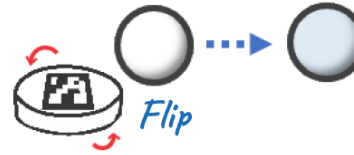
1

Show/Hide Node



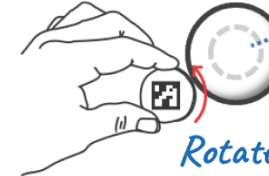
2

Reposition Node



3

Change Node State



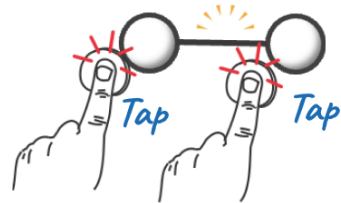
4

Scale Node



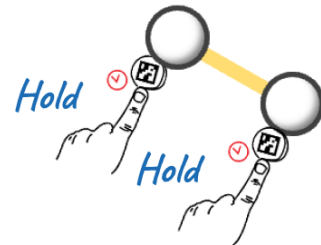
5

Highlight Node



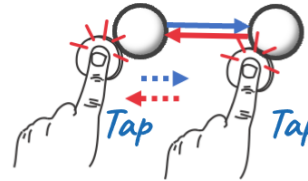
6

Show/Hide Link



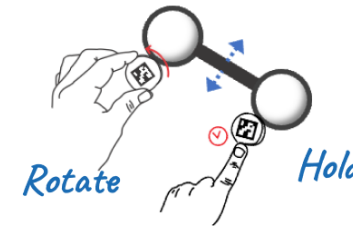
7

Change Link Type



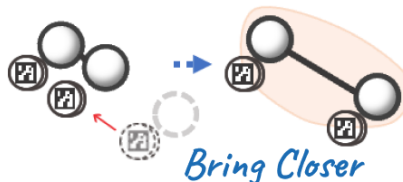
8

Change Link Direction



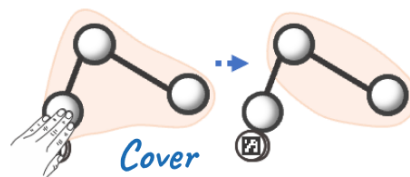
9

Change Link Scale



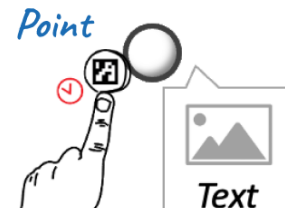
10

Grouping



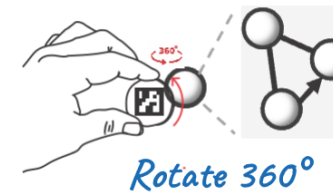
11

Ungrouping



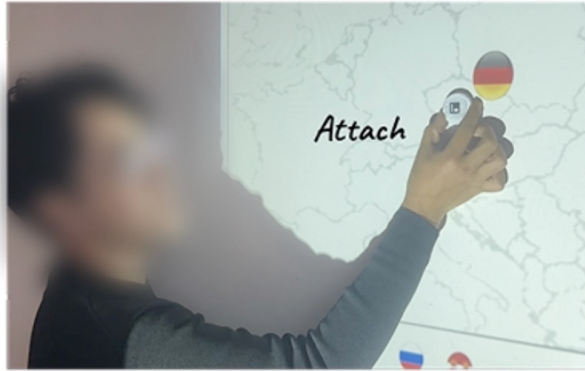
12

Show/Hide Annotation

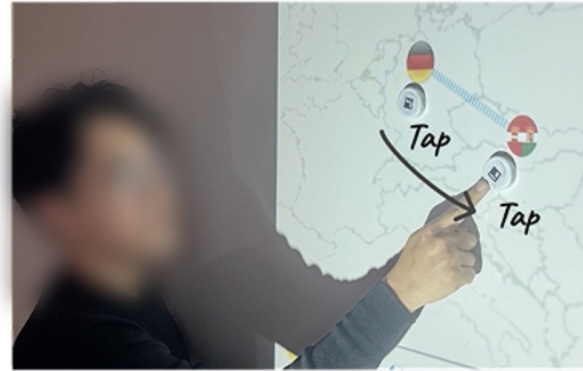


13

Show/Hide Child Network



Show/Hide Node



Show/Hide Link



Scale Node



Highlight Node



Change Node State



Show Annotation



Group/Ungroup Node



In the AI era, how can AI help in efficient and creative data storytelling creation?

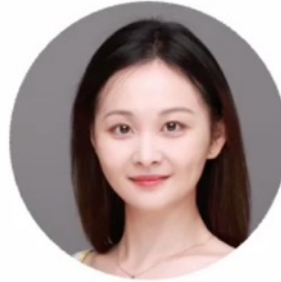


CHI 2024
Surfing the World
11-16 May 2024

Where Are We So Far? Understanding Data Storytelling Tools from the Perspective of Human-AI Collaboration



Haotian Li¹



Yun Wang²

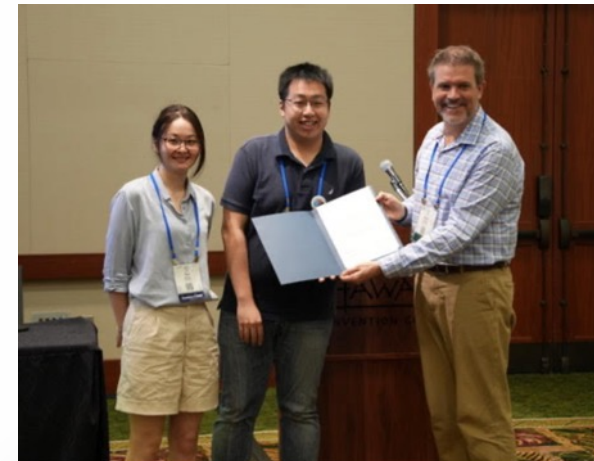


Huamin Qu¹



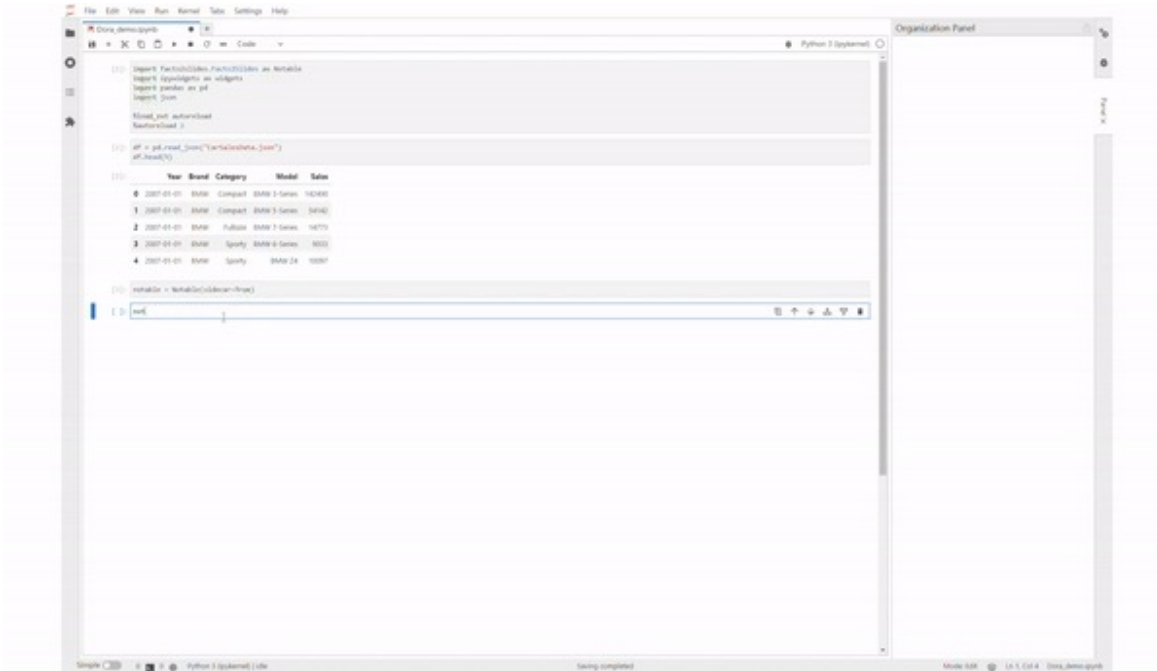
CHI 2024
Surfing the World
11-16 May 2024

Best Paper Honourable Mention



Where Are We So Far?

Improve data story creation efficiency



Data Science: Notable¹ (CHI '23),
InkSight² (VIS '23), OutlineSpark³ (CHI '24)



Sports: VisCommentator⁴ (VIS '21)

Where Are We So Far?

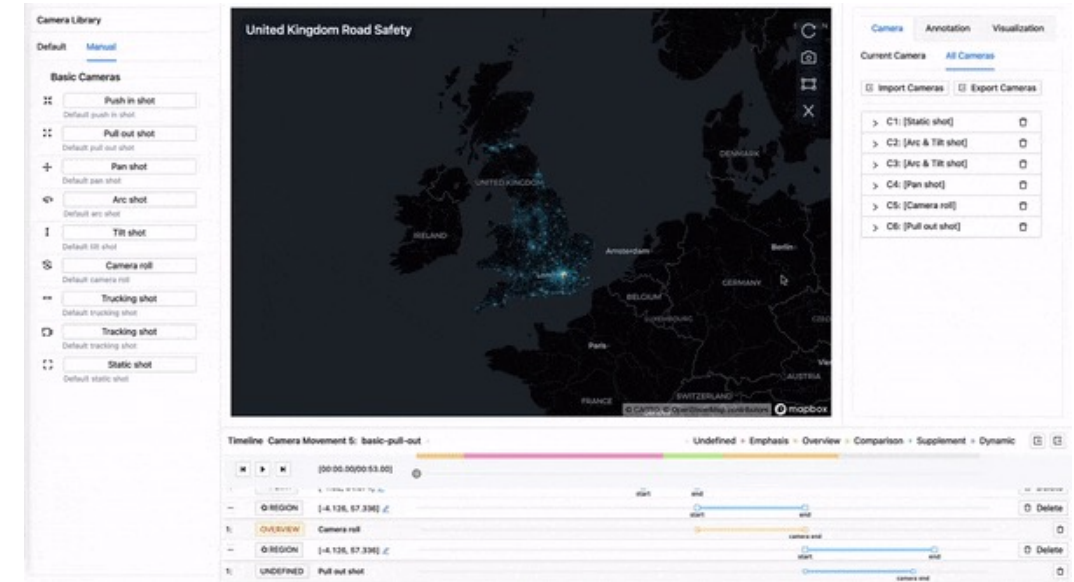
Unleash creativity in data storytelling



UTTERFLY

father

CAMEL



Animation: DancingWords⁵ (JoV '21), Wakey-Wakey⁶ (UIST '23),
Emordle⁷ (TVCG '23), Dynamic Typograph (ICCV '25)

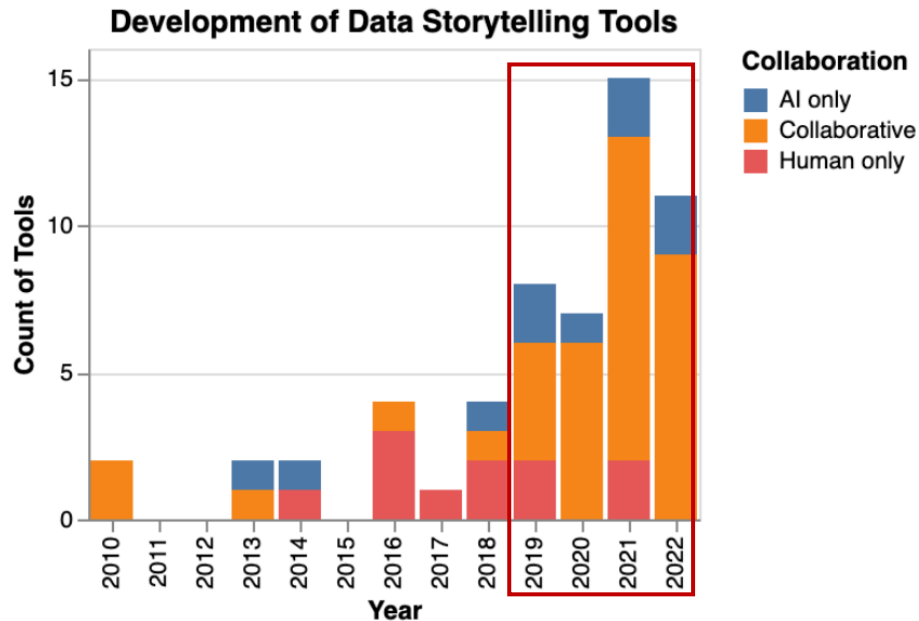
Cinematography: GeoCamera⁸ (CHI '23)

Where Are We So Far?

We provides a comprehensive review on how existing tools amplify humans' and AI's advantages through collaboration (CHI2024)²⁵.

Year	Tool	Analysis	Planning	Implementation	Communication
2016	Data-Driven Guides [51]	N/A	N/A	H-C	N/A
2017	ChartAccent [92]	N/A	N/A	H-C	N/A
2018	DataInk [139]	N/A	N/A	H-C	N/A
2019	Timeline Storyteller [7]	N/A	N/A	H-C	N/A
2020	Infomages [22]	N/A	N/A	H-C A-A	N/A
2020	DataQuilt [145]	N/A	N/A	H-C A-A	N/A
2021	Chartreuse [26]	N/A	N/A	H-C A-A	N/A
2021	InfoColorizer [144]	N/A	N/A	H-C A-A	N/A
2021	CAST [38]	N/A	N/A	H-C A-A	N/A
2022	Vistylst [103]	N/A	N/A	H-C A-A	N/A
2013	Contextifier [45]	N/A	N/A	A-C	N/A
2014	NewsViews [37]	N/A	N/A	A-C	N/A
2018	Metoyer <i>et al.</i> [80]	N/A	N/A	A-C	N/A
2019	Chen <i>et al.</i> [15]	N/A	N/A	A-C	N/A
2020	Retrieve-then-Adapt [90]	N/A	N/A	A-C	N/A
2021	AutoClips [100]	N/A	N/A	A-C	N/A
2021	Datamations [89]	N/A	N/A	A-C	N/A
2019	DataSelfie [50]	N/A	N/A	A-C H-A	N/A
2010	Click2Annotate [13]	N/A	N/A	A-C H-O	N/A
2010	Touch2Annotate [14]	N/A	N/A	A-C H-O	N/A
2018	Voder [108]	N/A	N/A	A-C H-O	N/A
2019	Text-to-Viz [27]	N/A	N/A	A-C H-O	N/A
2021	InfoMotion [129]	N/A	N/A	A-C H-O	N/A
2022	Infographics Wizard [120]	N/A	N/A	A-C H-O	N/A
2019	Fu <i>et al.</i> [36]	N/A	N/A	A-R	N/A
2022	Fan <i>et al.</i> [34]	N/A	N/A	A-R	N/A
2022	Liu <i>et al.</i> [72]	N/A	N/A	A-A	N/A
2014	Ellipsis [96]	N/A	H-C	H-C	N/A
2016	DataClips [3]	N/A	H-C	H-C	N/A
2021	Idyll Studio [23]	N/A	H-C	H-C	N/A
2021	VizFlow [111]	N/A	H-C	H-C A-A	N/A
2021	Kori [57]	N/A	H-C	H-C A-A	N/A
2021	Data Animator [116]	N/A	H-C	H-C A-A	N/A
2023	GeoCamera [67]	N/A	H-C	H-C A-A	N/A
2021	VisCommentator [17]	N/A	H-C	A-C H-O	N/A
2022	SmartShots [115]	N/A	H-C	A-C H-O	N/A
2022	Sportnesia [16]	N/A	H-C	A-C H-O	N/A
2023	DataParticles [9]	N/A	H-C	A-C H-O	N/A
2021	Gemini ² [52]	N/A	H-C A-A	H-C A-A	N/A
2020	Gravity [83]	N/A	H-C A-O	H-C	H-C
2022	Gravity++ [84]	N/A	H-C A-O	H-C	N/A
2021	ChartStory [146]	N/A	A-C H-O	A-C H-O	N/A
2016	CLUE [39]	H-C	H-C	H-C	H-C
2019	InsideInsights [78]	H-C	H-C	H-C	H-C
2021	ToonNote [48]	H-C	H-C	H-C	N/A
2018	InfoNice [132]	H-C	N/A	H-C	N/A
2023	Slide4N [124]	H-C	H-C A-A	A-C H-O	N/A
2022	NB2Slides [148]	H-C	A-C	A-C H-O	N/A
2019	DataToon [49]	H-C A-A	H-C	H-C A-A	N/A
2022	Erato [113]	H-C A-A	H-C A-A	A-C H-O	N/A
2023	Notable [64]	H-C A-A	A-C H-O	A-C H-O	N/A
2020	Brexble [21]	A-C	N/A	A-C H-A	N/A
2019	DataShot [131]	A-C	A-C H-O	A-C H-O	N/A
2016	TSI [8]	A-C H-A	A-C H-O	A-C H-O	N/A
2020	Calliope [101]	A-C H-O	A-C H-O	A-C H-O	N/A
2020	data2video [75]	A-C H-O	A-C H-O	A-C H-A	N/A
2021	Lu <i>et al.</i> [74]	A-C H-O	A-C H-O	A-C H-O	N/A
2022	Roslingifier [104]	A-C H-O	A-C H-O	A-C H-O	N/A
2013	SketchStory [58]	N/A	N/A	N/A	H-C A-A
2022	Hall <i>et al.</i> [40]	N/A	N/A	N/A	H-C A-A

Human-AI Collaborative Tools



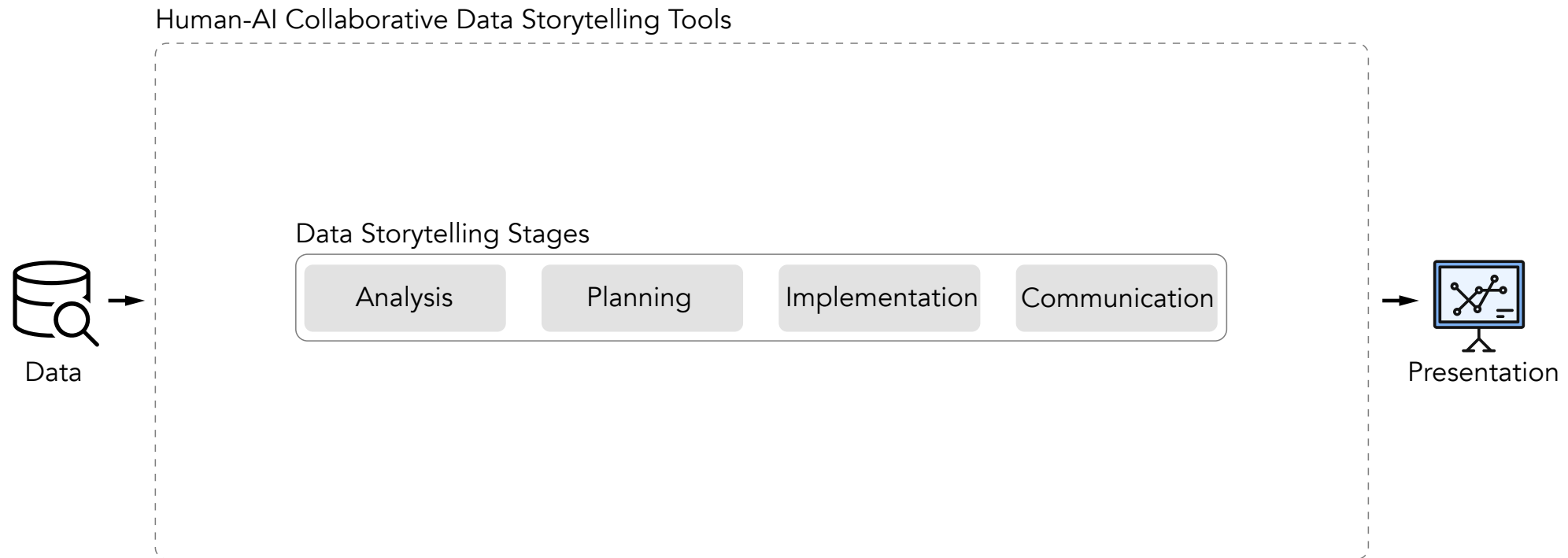
- We collected 60 tools between 2010 and 2023 in top HCI and visualization venues.
- Since 2019, human-AI collaborative tools have gained interest from researchers.

We need a systematic reflection to review the research progress and ignite new ideas with powerful AI systems.

Characterizing Human-AI Collaboration

We characterize human-AI collaborative data storytelling tools from:

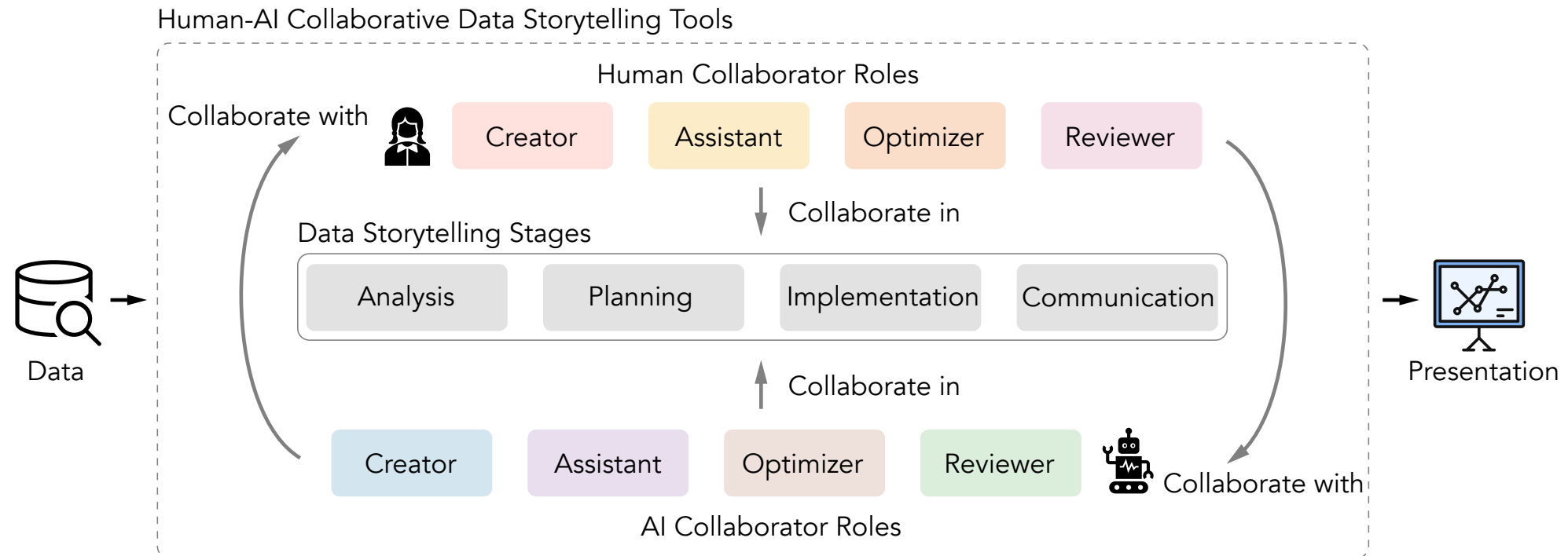
- The covered stages in the workflow to contextualize the collaboration



Characterizing Human-AI Collaboration

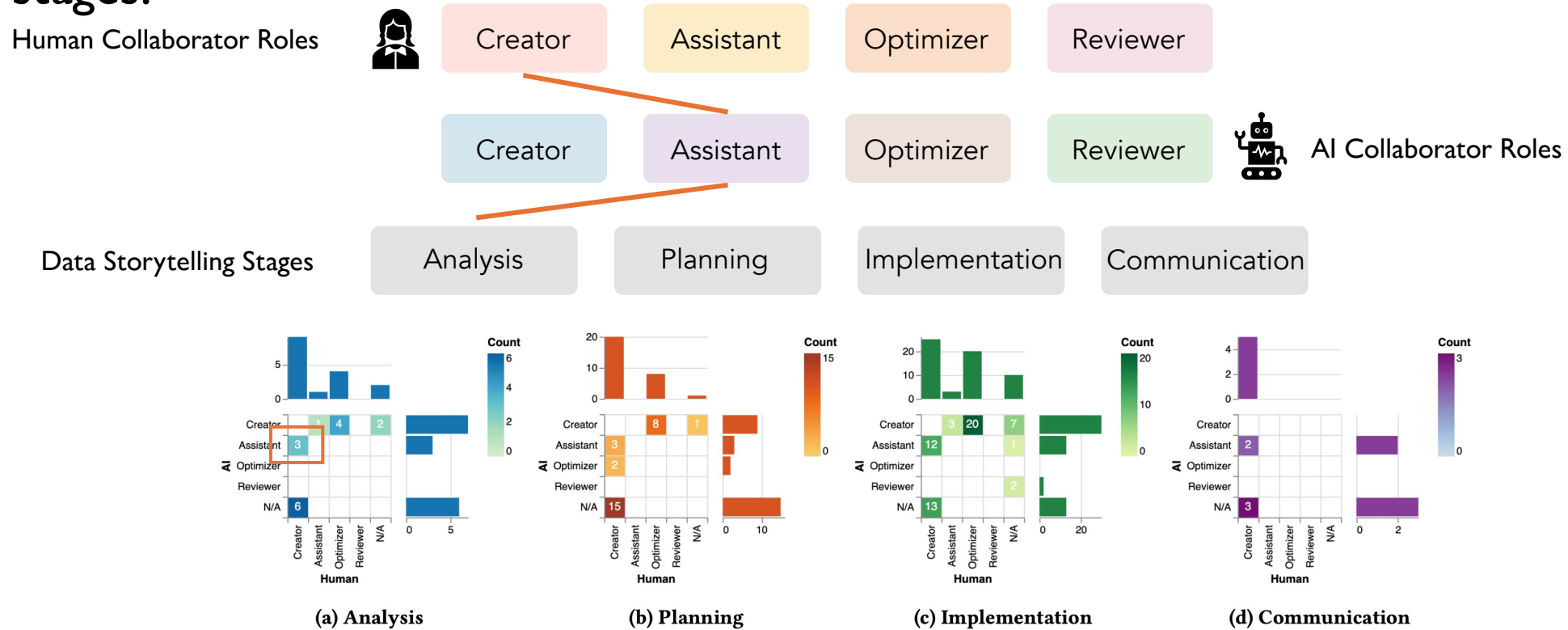
We characterize human-AI collaborative data storytelling tools from:

- The covered stages in the workflow to contextualize the collaboration
- Humans' and AI's roles in each stage to reflect the work distribution and their advantages and disadvantages



Observations and Lessons

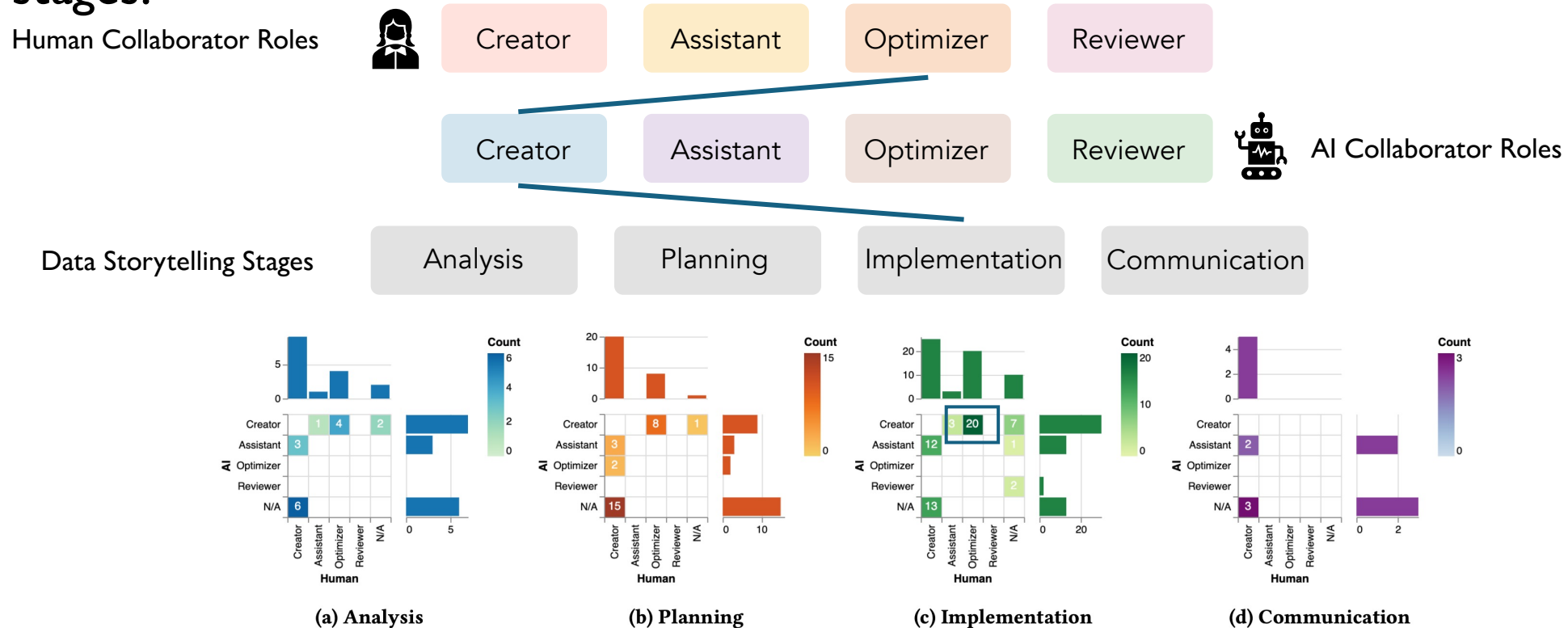
We identify common collaboration patterns between two roles in individual stages.



Human creators often receive assistance from AI in the analysis stage.

Observations and Lessons

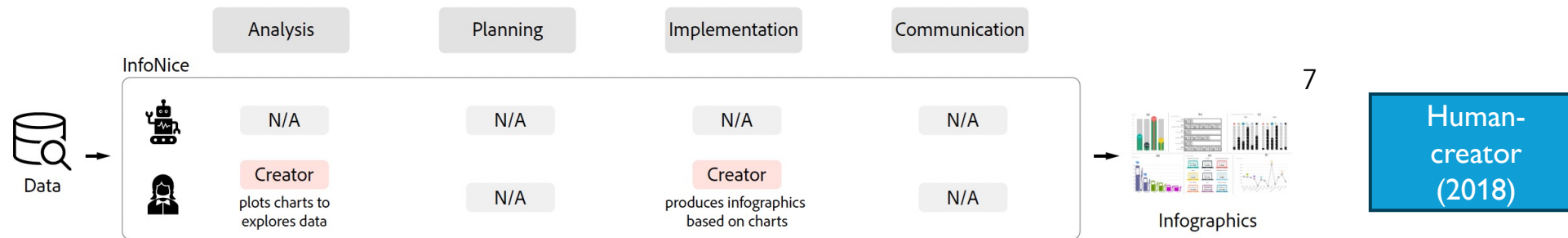
We identify common collaboration patterns between two roles in individual stages.



AI creators often collaborate with human optimizers at the implementation stage.

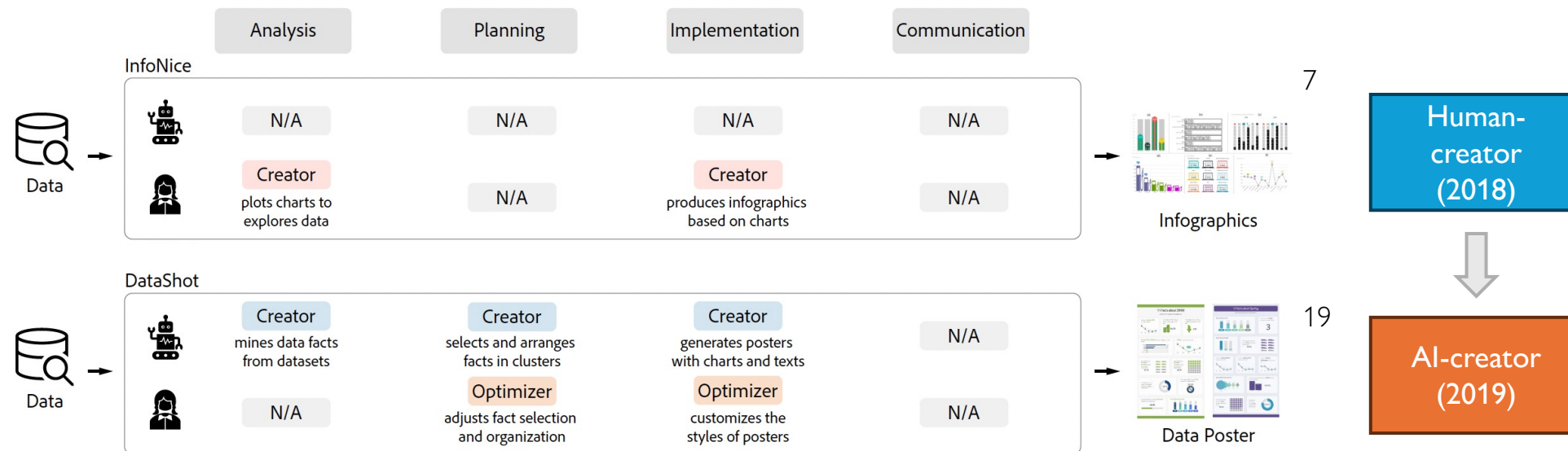
Observations and Lessons

Beyond collaboration in an individual stage, we notice an interesting trace when investigating the collaboration across all stages:



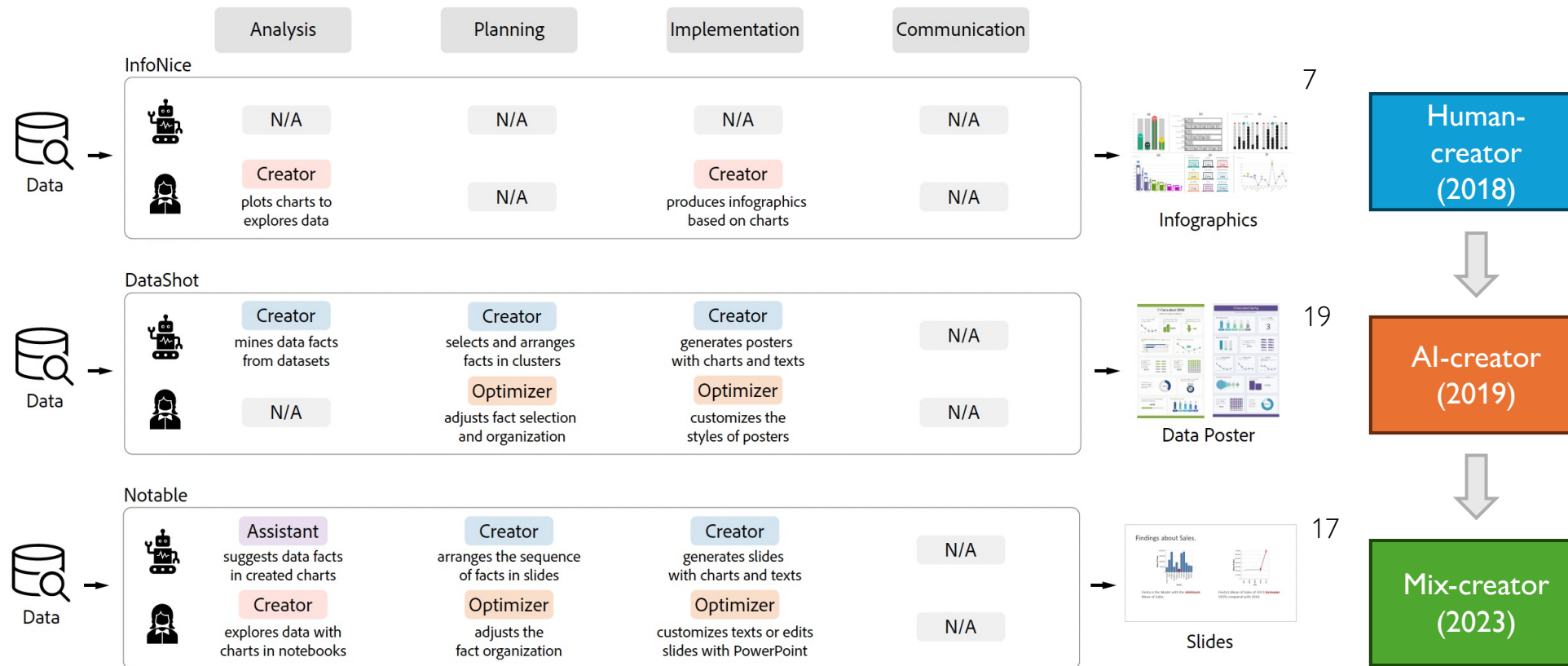
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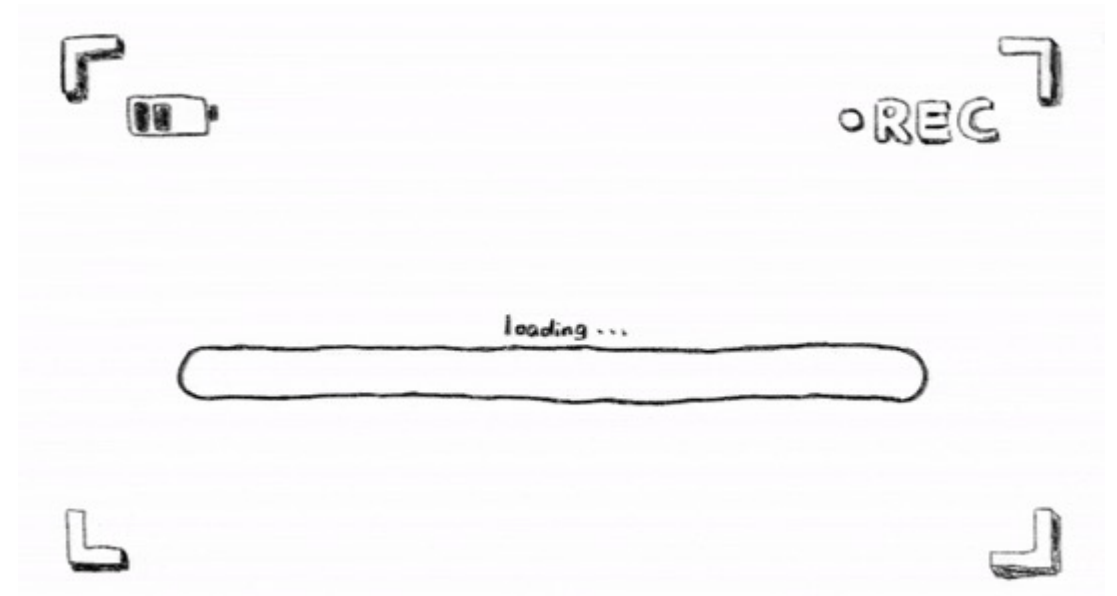
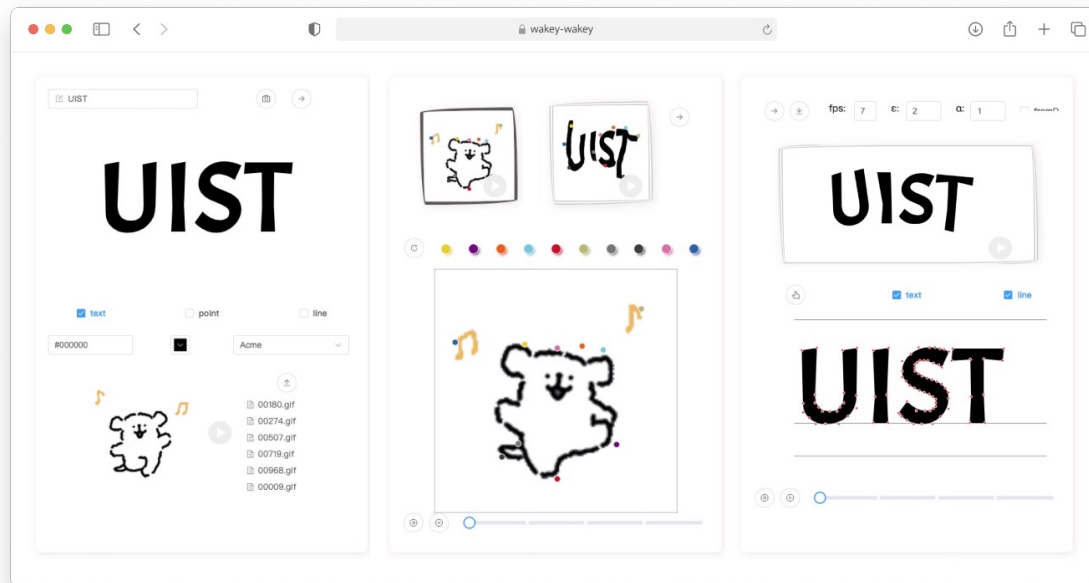
Observations and Lessons

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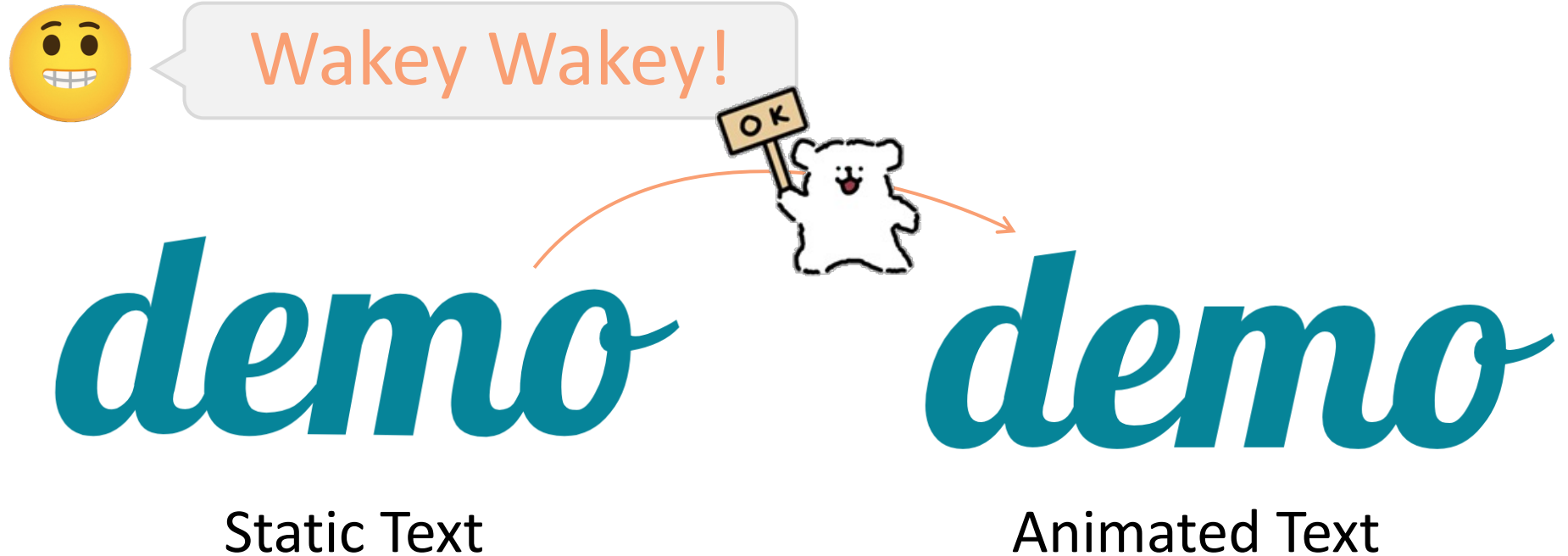
Creative Design of Animated Text

- Leverage AI to transfer motion design



L. Xie, Z. Zhou, K. Yu, Y. Wang, H. Qu, S. Chen. 2023. Wakey-Wakey: Animate Text by Mimicking Characters in a GIF. Proc. *UIST*.

Creative Design of Animated Text



A camel walks steadily across the desert

CAMEL

Dynamic Typography: Bringing Text to Life via Video Diffusion Prior

Zichen Liu *, Yihao Meng *, Hao Ouyang, Yue Yu, Bolin Zhao,
Daniel Cohen-Or, Huamin Qu

*IEEE/CVF International Conference on Computer Vision (ICCV),
2025*

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Stars

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Establishment of Division of Arts and Machine Creativity

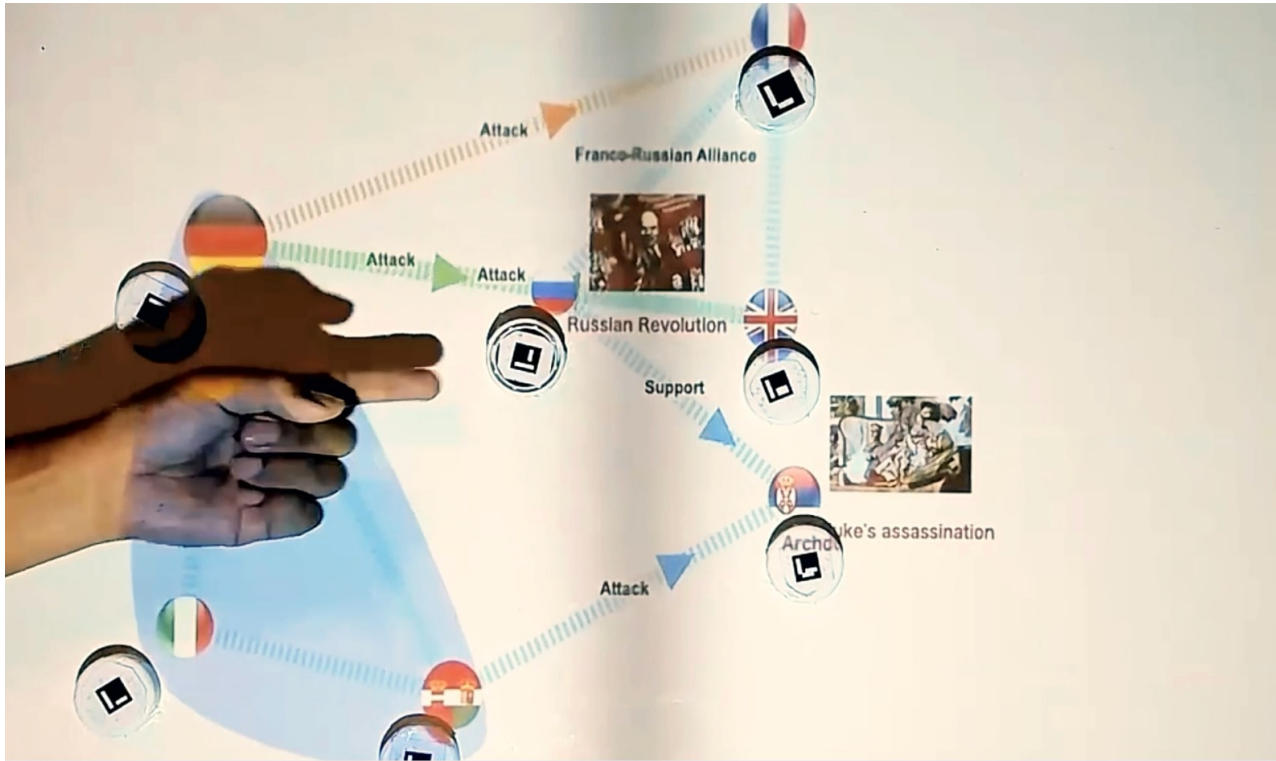


Conclusions

- AI can help with graph visualization in many aspects, such as style transfer, layout generation, and more.
- Communication will be more important than analytics, and storytelling is key.
- Human-AI co-creation is a growing trend.



Thank you!



Learn more about our latest research by scanning the QR code

Contact: huamin@cse.ust.hk