Hoorcollege 4
Visualisaties in rapporten
Interactieve visualisaties

Informatie-uitwisseling: informatievisualisatie

Jeroen Ooge

Universiteit Utrecht

Overzicht hoorcolleges

Hoorcollege 1
Algemene principes en vis-types

Hoorcollege 2
Theoretische fundamenten van vis

Hoorcollege 3
Inleiding ggplot2 + hoe vis kan misleiden

Hoorcollege 4
Vis in rapporten + interactieve vis

De semiotische ladder voor vis

SOCIAL WORLD:
beliefs, expectations, commitments,
contracts, social laws, culture, ...

PRAGMATICS:
intentions, communication, conversations,
negotiations, speech acts, ...

SEMANTICS:
meanings, propositions, validity,
truth, signification, denotations, ...

SYNTACTICS:
formal structure, language, logic,
data, records, deduction, software, files, ...

EMPIRICS:
pattern, variety, noise, entropy, channel capacity, codes,
efficiency, redundancy, ...

PHYSICAL WORLD:
signals, traces, physical destinctions, hardware, physical tokens,
component density, speeds, economics, laws of nature,...

communicatie
met vis

vertaling
naar vis

data
verzamelen

Hoorcollege 4

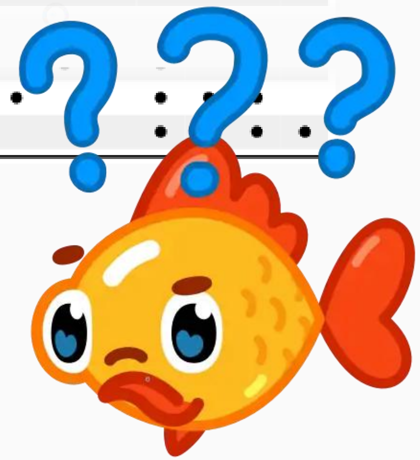
Visualisaties in rapporten
Interactieve visualisaties

1. Vis in rapporten
2. Interactieve vis
3. Tentamen

6 tips om je rapporten te verbeteren met vis-principes

Tip 1: Maak tabellen inzichtelijk

	ACTIVITY		ALGORITHM										INTERACTION							
	Interpretation	Prediction	Anomaly detection	Artificial neural network	Classical statistics	Classification	Clustering/similarity	Data mining	Dimension reduction	Feature selection	Segmentation	Other	Abstract/elaborate	Connect	Encode	Explore	Filter	Reconfigure	Select	Shepherd
Abbasloo et al. (2019)	●				●									●	●	●			●	●
Abdullah et al. (2020)	●						●		●				●	●			●	●	●	●
Afzal et al. (2011)		●										●	●			●			●	●
Yu et al. (2017)	●		●		●		●		●				●	●			●	●	●	
Zhao et al. (2017)	●							●					●				●		●	●



Hoe kun je patronen verduidelijken?

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Afzal et al. (2011)		●										●	●			●			●	●
Alsaad et al. (2019)		●		●		●							●							
Barlowe et al. (2013)	●						●								●			●	●	●
Behrisch et al. (2018)	●						●					●	●		●	●				
Borland et al. (2020)	●						●						●		●					●
Brunker et al. (2019)	●				●		●							●	●		●	●	●	●
Cao et al. (2011)	●						●						●	●				●	●	●
Clark et al. (2017)	●				●								●						●	●
Dang et al. (2015)	●						●						●	●				●	●	
Dingen et al. (2019)		●			●								●					●	●	●
Dixit et al. (2017)	●					●		●							●		●	●	●	●
Fang et al. (2017)	●							●					●				●	●		
Farag et al. (2015)	●						●		●					●			●	●	●	
Feller et al. (2018)	●						●								●		●			●
Geurts et al. (2015)	●						●				●		●						●	
Gotz et al. (2011)	●						●						●	●				●	●	●
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Gotz et al. (2020)	●				●		●						●		●		●	●	●	●
Guo et al. (2020)	●			●			●		●				●	●					●	
Guo et al. (2018)	●						●						●	●			●	●	●	●
Herold et al. (2010)	●					●													●	
Hinterberg et al. (2015)	●				●												●		●	
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Huang et al. (2019)		●					●						●						●	
Hund et al. (2016)	●						●		●				●	●	●	●	●	●	●	●
Hur et al. (2020)		●		●				●					●				●		●	
Ji et al. (2017)	●								●				●	●		●	●	●	●	●
Ji et al. (2019a)	●						●		●				●	●		●		●	●	
Ji et al. (2019b)	●			●	●		●		●						●		●	●	●	●
Jönsson et al. (2019)	●				●									●		●	●			
Kakar et al. (2019)	●							●					●	●			●	●	●	
Klemm et al. (2014)	●						●							●					●	
Klimov et al. (2015)	●							●					●				●	●		
Kovalerchuk et al. (2012)		●						●					●		●	●		●	●	
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Krause et al. (2018)		●				●							●				●			
Kumar et al. (2015)	●				●		●			●			●	●			●	●	●	
Kwon et al. (2018)	●				●		●		●				●	●	●	●	●	●	●	●
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Kwon et al. (2020)	●							●				●	●	●	●		●	●	●	
L'Yi et al. (2015)	●						●						●	●			●	●	●	
L'Yi et al. (2017)		●			●								●	●	●	●	●	●	●	●
Lamy and Tsopra (2019)		●		●														●	●	
Li et al. (2012)	●				●		●		●				●	●		●	●		●	●
Li et al. (2020)		●		●					●				●	●					●	●
Liao et al. (2017)	●		●			●			●				●	●		●	●		●	
Males et al. (2020)	●				●						●		●	●					●	
Malik et al. (2015)	●				●								●				●	●		
Moschonas et al. (2016)	●						●													●
Müller et al. (2020)	●											●	●			●	●	●	●	
Nauta et al. (2020)		●		●		●			●								●		●	●
Nguyen et al. (2011)	●					●	●		●	●			●	●		●	●		●	
Nguyen et al. (2012)	●				●	●	●		●					●		●	●	●	●	
Raidou et al. (2016a)	●					●			●					●	●				●	
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Riegler et al. (2016)	●						●						●					●	●	●
Santamaría et al. (2008)	●						●						●	●			●		●	
Santamaría et al. (2019)	●							●					●	●		●				●
Seo and Shneiderman (2002)	●						●						●	●					●	
Song et al. (2017)	●				●		●							●	●	●	●	●	●	
Spitz et al. (2020)		●				●									●			●	●	●
Stolper et al. (2014)	●							●					●	●		●	●	●	●	
Verma et al. (2017)		●			●		●						●				●	●	●	
Von Landesberger et al. (2013)	●						●		●		●			●					●	
Widanagamaachchi et al. (2017)	●				●		●						●		●					
Xing et al. (2014)	●				●		●						●		●		●		●	
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Zhao et al. (2017)	●							●					●				●		●	●

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Yu et al. (2017)	•		•		•		•		•				•	•			•	•	•	
Zhao et al. (2017)	•							•					•				•		•	•
Total	55	16	2	8	20	11	38	11	18	3	4	5	51	38	20	19	41	38	58	32

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6.1.1. Domain	198
Biology	28
Business	19
Computer Vision	59
Computers	6
Health	30
Humanities	41
Nutrition	8
Simulation	8
Social / Socioeconomic	22
Other	93

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2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
1	2	2	–	2	1	–	–	–	–	–
–	–	–	–	–	–	2	–	2	6	5
1	3	2	3	4	4	7	14	8	1	–
9	3	3	7	5	5	5	2	4	–	–
–	–	–	–	–	–	2	7	12	12	6
–	–	–	–	–	–	3	4	10	12	8
–	1	4	3	2	2	1	–	–	–	–
1	1	1	1	3	2	4	5	7	4	–
1	1	2	3	–	2	11	1	1	–	–
1	1	6	7	7	2	3	3	4	3	–
1	1	3	1	2	1	4	1	–	–	–
–	–	1	–	3	1	12	9	7	1	–
–	–	–	–	–	1	2	–	–	–	2
–	1	–	–	–	1	2	4	2	6	9
–	–	–	–	1	–	5	–	5	12	2
–	1	1	2	1	1	7	4	1	–	–
–	2	1	1	2	1	–	–	–	–	–
–	1	1	–	–	–	4	4	5	5	–
15	18	27	28	32	24	74	58	68	62	32

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Tip 1: Maak tabellen inzichtelijk

	P7	P2	P3	P8	P6	P5	P10	P9	P1	P4
Understanding the visualisation										
Past fit and uncertainty are not understood	•	•								
Need for control										
More control over the prediction model						•			•	•
Need for comparisons										
Comparing countries is relevant	•			•				•	•	
Comparing products is relevant			•			•	•	•	•	
Comparing prediction models is relevant				•					•	
Need for tailored explanations										
Explaining the past data									•	
Explaining the model's development process		•			•	•			•	•
Explaining the prediction model						•	•			•
Understanding the algorithmic level										
Visual components gradually improve mental model						•	•			

Hoe kun je inzichten koppelen aan info over de deelnemers?

Jeroen Ooge and Katrien Verbert. 2022. Visually Explaining Uncertain Price Predictions in Agrifood: A User-Centred Case-Study. *Agriculture* 12, 7: 1024. https://doi.org/10.3390/agriculture12071024

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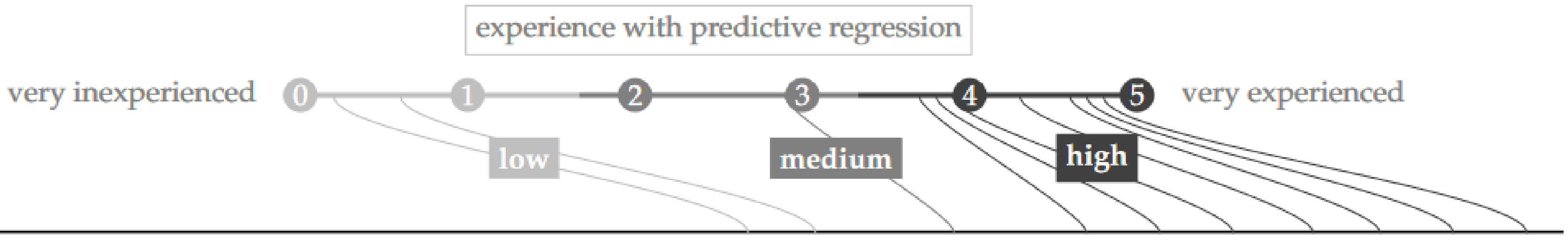

	P7	P2	P3	P8	P6	P5	P10	P9	P1	P4
Understanding the visualisation										
Past fit and uncertainty are not understood	•	•								
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Comparing countries is relevant	•			•				•	•	
Comparing products is relevant			•			•	•	•	•	
Comparing prediction models is relevant				•					•	
Need for tailored explanations										
Explaining the past data									•	•
Explaining the model's development process		•			•	•			•	•
Explaining the prediction model		•	•	•		•	•		•	•

Jeroen Ooge and Katrien Verbert. 2022. Visually Explaining Uncertain Price Predictions in Agrifood: A User-Centred Case-Study. *Agriculture* 12, 7: 1024.
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Tip 2: Structureer met kleur

prices and uncertainty in the predictions. We evaluated
who are active in different parts of agrifood; collecting
quantitative data. In particular, we focused on the follo

RQ1 **Usability**: How user-friendly are the interaction
in our visual DSS?

RQ2 **Usefulness and needs**: How useful is our visual
the needs of people active in agrifood?

RQ3 **Model understanding**: How does visualising u
understanding of the prediction model underlyin

RQ4 **Trust**: How does visualising uncertain predicti
diction model underlying our visual DSS?

Our research contribution consists of extensively e
perspectives. First, considering our prototype as a pro

agriculture

MDPI

Article

Visually Explaining Uncertain Price Predictions in Agrifood: A User-Centred Case-Study

Jeroen Ooge * and **Katrien Verbert**

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Abstract: The rise of 'big data' in agrifood has increased the need for decision support systems that harvest the power of artificial intelligence. While many such systems have been proposed, their uptake is limited, for example because they often lack uncertainty representations and are rarely designed in a user-centred way. We present a prototypical visual decision support system that incorporates price prediction, uncertainty, and visual analytics techniques. We evaluated our prototype with 10 participants who are active in different parts of agrifood. Through semi-structured interviews and questionnaires, we collected quantitative and qualitative data about four metrics: usability, usefulness and needs, model understanding, and trust. Our results reveal that the first three metrics can directly and indirectly affect appropriate trust, and that perception differences exist between people with diverging experience levels in predictive modelling. Overall, this suggests that user-centred approaches are key for increasing uptake of visual decision support systems in agrifood.

Keywords: visual analytics; visualisation; uncertainty; explainable artificial intelligence; decision support systems; mixed-methods; thematic analysis

check for updates

Citation: Ooge, J.; Verbert, K. Visually Explaining Uncertain Price Predictions in Agrifood: A User-Centred Case-Study. *Agriculture* **2022**, *12*, 1024. https://doi.org/10.3390/agriculture12071024

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1. Introduction

Under the impulse of success stories in other domains, artificial intelligence and 'big data' are on the rise in agrifood [1], leading to promising research directions such as *Agriculture 4.0* [2] and the broader *Agrifood 4.0* [3], *precision agriculture* [4–6], and *smart farming* [7–9]. While the adoption of such technologies is still modest in real-life agrifood applications [10], it is expected that the wide availability of cloud computing and remote sensing [11] will further boost their spread [12]. To process the explosive amount of information in this era of growing digitisation and to make data-grounded decisions, agrifood stakeholders increasingly need the assistance of *decision support systems* (DSSs) [2] that facilitate learning and allow to modify decision processes by integrating domain knowledge, rather than systems that merely prescribe actions [13,14].

Yet, even though the need for DSSs in agrifood has been acknowledged for over two decades [13] and many prototypes have been proposed [2,15], the uptake of these systems has been limited so far. Parker et al. [16,17], Zhai et al. [2], and Rose et al. [18] discussed several reasons for this low uptake: user interfaces of DSSs are not always user-friendly and lack visualisations, DSSs are not necessarily relevant when they do not meet end users' needs or decision-making styles, outputs often miss uncertainty representations, and end users often distrust DSSs with opaque underlying algorithms. In other words, developers of DSSs for agrifood face important design challenges such as increasing usability, guarding usefulness for end users, and raising appropriate trust in underlying decision models.

Tackling these challenges requires human-centred approaches, which lie at the core of *human–computer interaction* (HCI), an interdisciplinary field that connects computer science, social sciences, and technology-applying domains such as agrifood. Specifically, HCI studies how interfaces can be designed and tailored to specific end users or application contexts to improve user experience, for example [19–21]. Two subdomains of HCI specialise in visualising complex information and explaining artificial intelligence, respectively.

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Tip 2: Structureer met kleur

very inexperienced 0

thinking out loud (*Explore the new component in the visualisation. Explain what you see. What grabs your attention?*); (2) we asked them about their **trust** and **model understanding** (*Do you trust the prediction model? Do you understand how the prediction model works? Which parts of the visualisation made you say that?*); and (3) we quantitatively measured their trust.

Finally, after completing all scenarios, participants report[ed] four concepts related to predictive modelling and answered ad[...] **model understanding** and **usefulness** (*Which combination(s)* [...] *most useful to get insights into the prediction model? Would you like to* [...]

phisticated models. Still, P1 emphasised: "*[I] would expect each model to be discussed: why does this model predict different values from another one and the reasoning behind that*".

Need for tailored explanations: participants required tailored explanations about different aspects with different levels of detail.

Participants brought up four different aspects for which they needed explanations, and, interestingly, Table 2 shows that these participants had low to high experience with

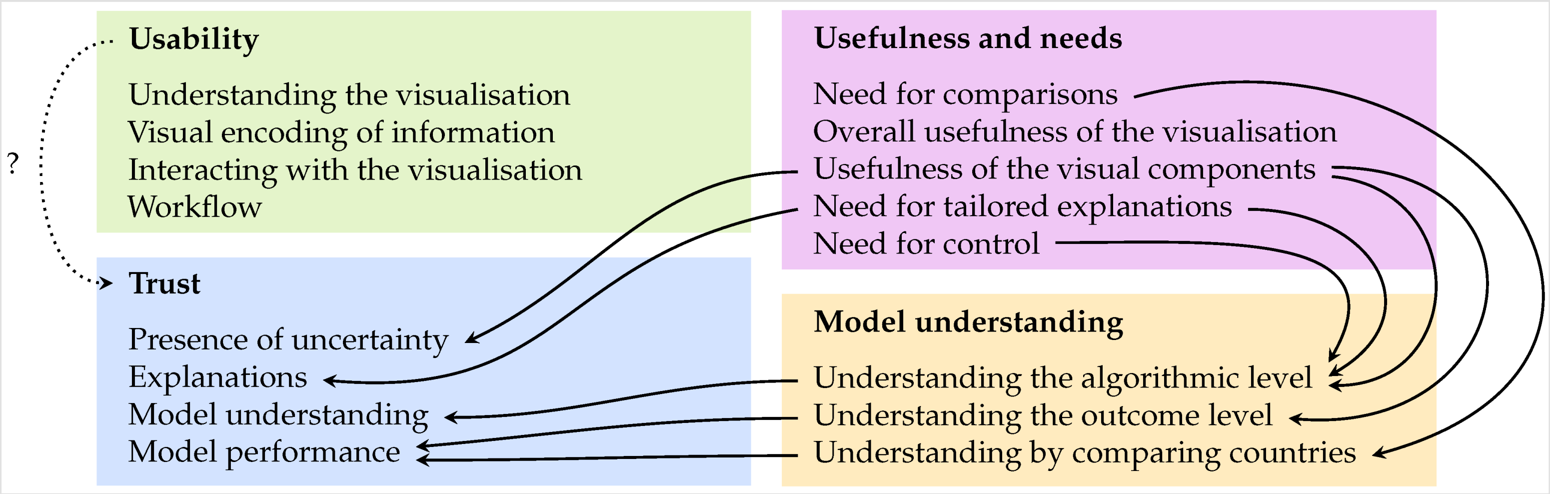
Understanding the visualisation
Past fit and uncertainty are not understood

Need for control
More control over the prediction model

Need for comparisons
Comparing countries is relevant
Comparing products is relevant
Comparing prediction models is relevant

Need for tailored explanations
Explaining the past data
Explaining the model's development process
Explaining the prediction model

Understanding the algorithmic level
Visual components gradually improve mental model



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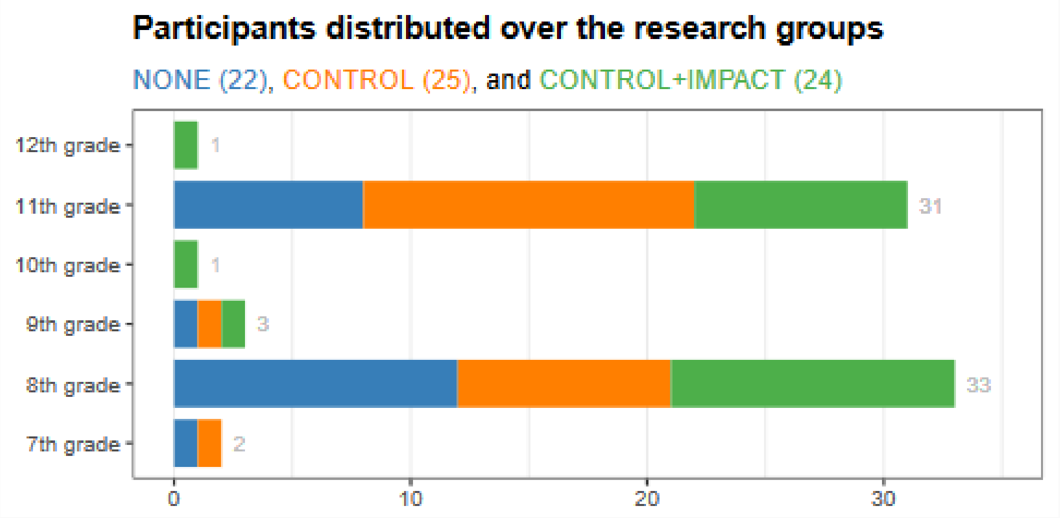
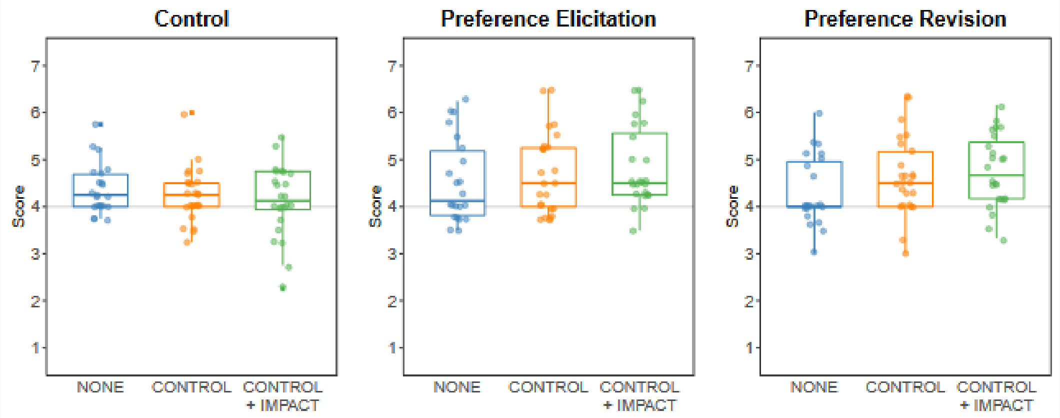
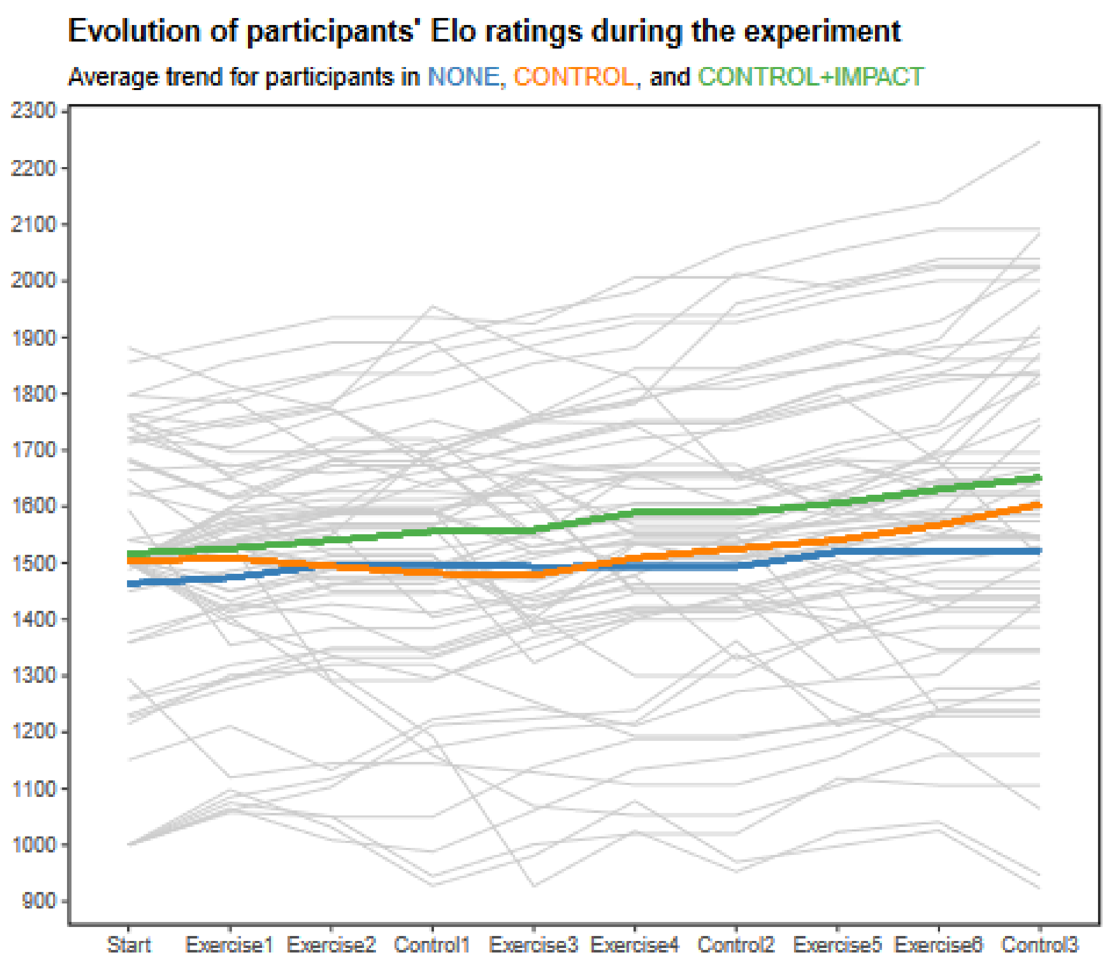
Tip 3: Gebruik kleuren consistent

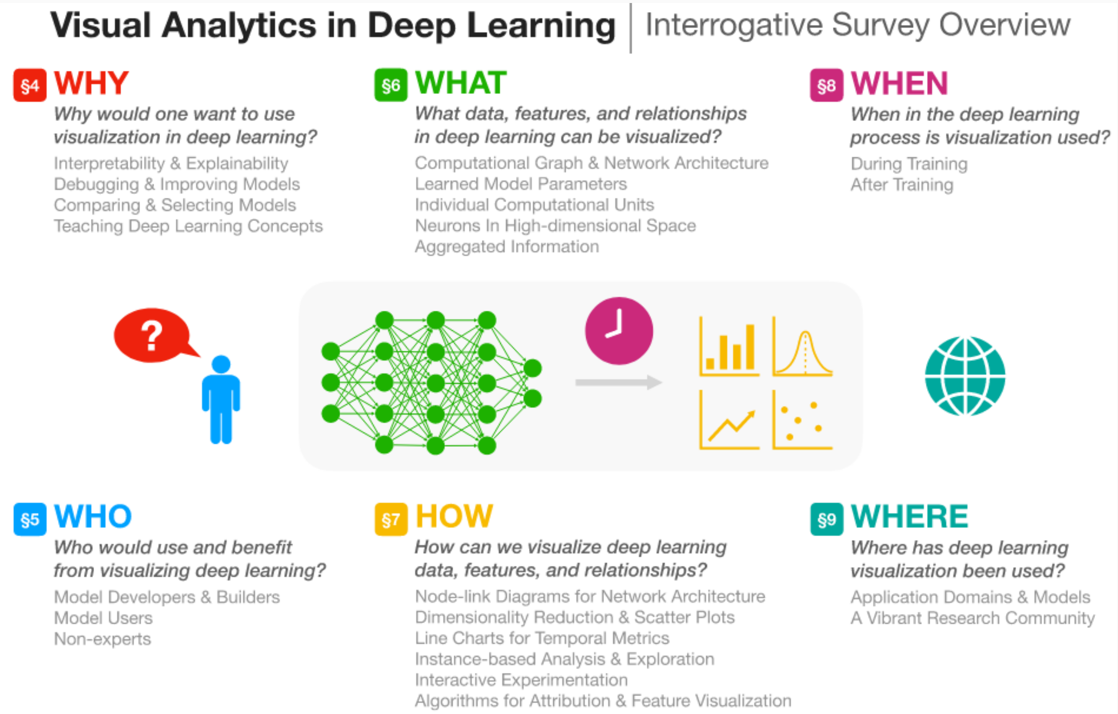






Jeroen Ooge, Leen Dereu, and Katrien Verbert. 2023. Steering Recommendations and Visualising Its Impact: Effects on Adolescents' Trust in E-Learning Platforms. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (IUI '23), 156–170. https://doi.org/10.1145/3581641.3584046

Tip 3: Gebruik kleuren consistent



To interpret representations learned by deep models (why), model developers (who) visualize neuron activations in convolutional neural networks (what) using t-SNE embeddings (how) after the training phase (when) to solve an urban planning problem (where).

where) is given its own section for discussion, ordered to best motivate why visualization and visual analytics in deep learning is such a rich and exciting area of research.

§ 4 Why do we want to visualize deep learning?
Why and for what purpose would one want to use visualization in deep learning?

§ 5 Who wants to visualize deep learning?
Who are the types of people and users that would use and stand to benefit from visualizing deep learning?

§ 6 What can we visualize in deep learning?
What data, features, and relationships are inherent to deep learning that can be visualized?

§ 7 How can we visualize deep learning?
How can we vi
tures, and relatio

§ 8 When can we vi
When in the d
used and best su

§ 9 Where is deep le
Where has deep

Section 10 present
lems that we gathered
vey. Section 11 conclu

	WHY				WHO			WHAT					HOW						WHEN		WHERE
Work	4.1 Interpretability & Explainability	4.2 Debugging & Improving Models	4.3 Comparing & Selecting Models	4.4 Teaching Deep Learning Concepts	5.1 Model Developers & Builders	5.2 Model Users	5.3 Non-experts	6.1 Computational Graph & Network Architecture	6.2 Learned Model Parameters	6.3 Individual Computational Units	6.4 Neurons in High-dimensional Space	6.5 Aggregated Information	7.1 Node-link Diagrams for Network Architecture	7.2 Dimensionality Reduction & Scatter Plots	7.3 Line Charts for Temporal Metrics	7.4 Instance-based Analysis & Exploration	7.5 Interactive Experimentation	7.6 Algorithms for Attribution & Feature Visualization	8.1 During Training	8.2 After Training	9.2 Publication Venue
Abadi, et al., 2016 [27]	●	●	●		●	●						●			●				●	●	arXiv
Bau, et al., 2017 [28]	●		●		●					●						●		●		●	CVPR
Bilal, et al., 2017 [29]	●	●			●					●		●				●		●	●		TVCG
Bojarski, et al., 2016 [30]	●	●			●				●			●				●		●	●	●	arXiv

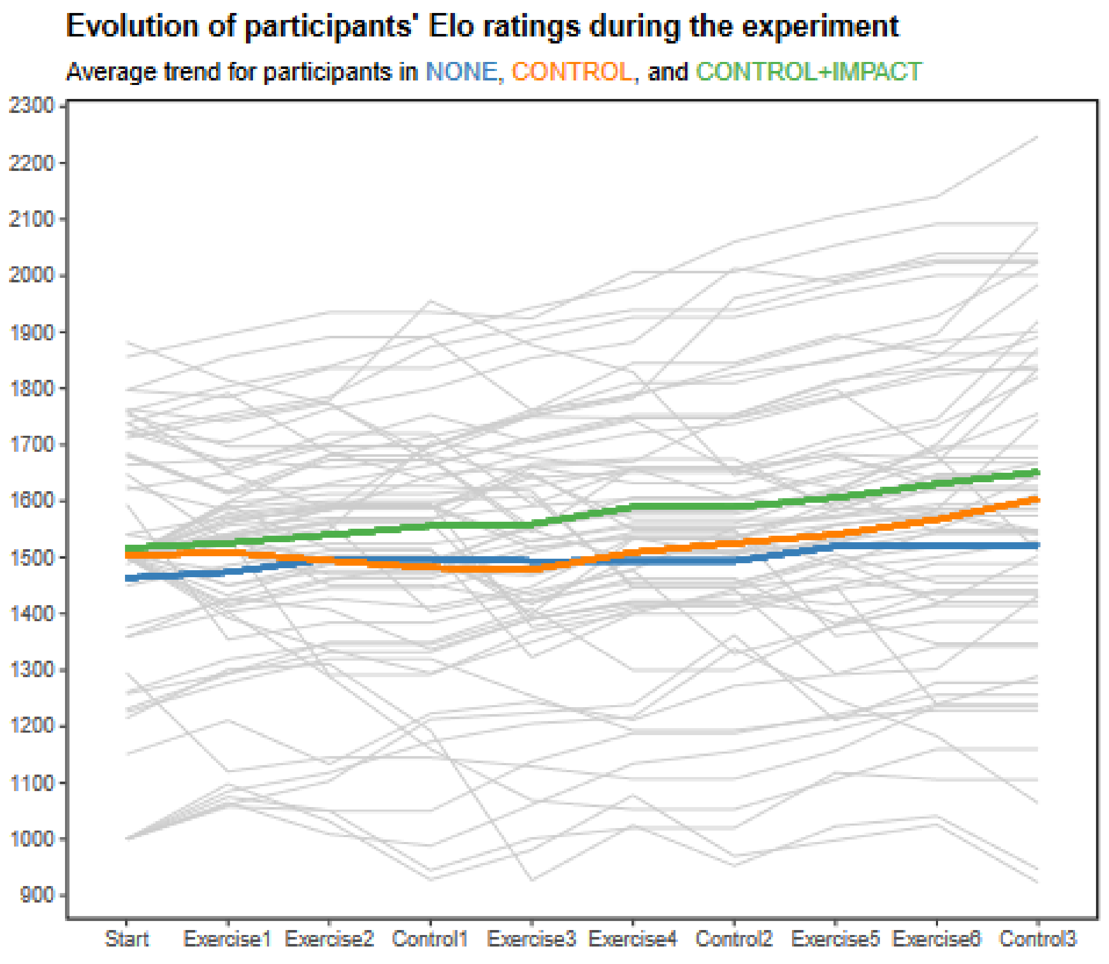
Fred Hohman, Minsuk Kahng, Robert Pienta, and Duen Horng Chau. 2019. Visual Analytics in Deep Learning: An Interrogative Survey for the Next Frontiers. *IEEE Transactions on Visualization and Computer Graphics* 25, 8: 2674–2693. https://doi.org/10.1109/TVCG.2018.2843369

Tip 4: Onderdruk bijzaken

Table 1: Comparing the research groups with t-tests (Mann-Whitney U test for one-dimensional trust). Cells contain the effect sizes (second group mean minus first group mean).

	NONE VS. CONTROL	NONE VS. CONTROL+IMPACT	CONTROL VS. CONTROL+IMPACT
Benevolence	0.16 ($p = 0.263$)	0.61 ($p = 0.011$)	0.45 ($p = 0.035$)
Trusting beliefs	-0.01 ($p = 0.529$)	0.38 ($p = 0.042$)	0.40 ($p = 0.030$)
Transparency	0.29 ($p = 0.068$)	1.04 ($p = 0.000$)**	0.74 ($p = 0.002$)*
One-dimens. trust	0.00 ($p = 0.504$)	0.78 ($p = 0.017$)	0.78 ($p = 0.020$)
Multidimens. trust	0.15 ($p = 0.207$)	0.55 ($p = 0.009$)*	0.40 ($p = 0.039$)
Preference revision	0.33 ($p = 0.080$)	0.43 ($p = 0.030$)	0.10 ($p = 0.325$)

*$p < 0.01$, **$p < 0.001$, non-significant results ($p \geq 0.5$) are greyed out



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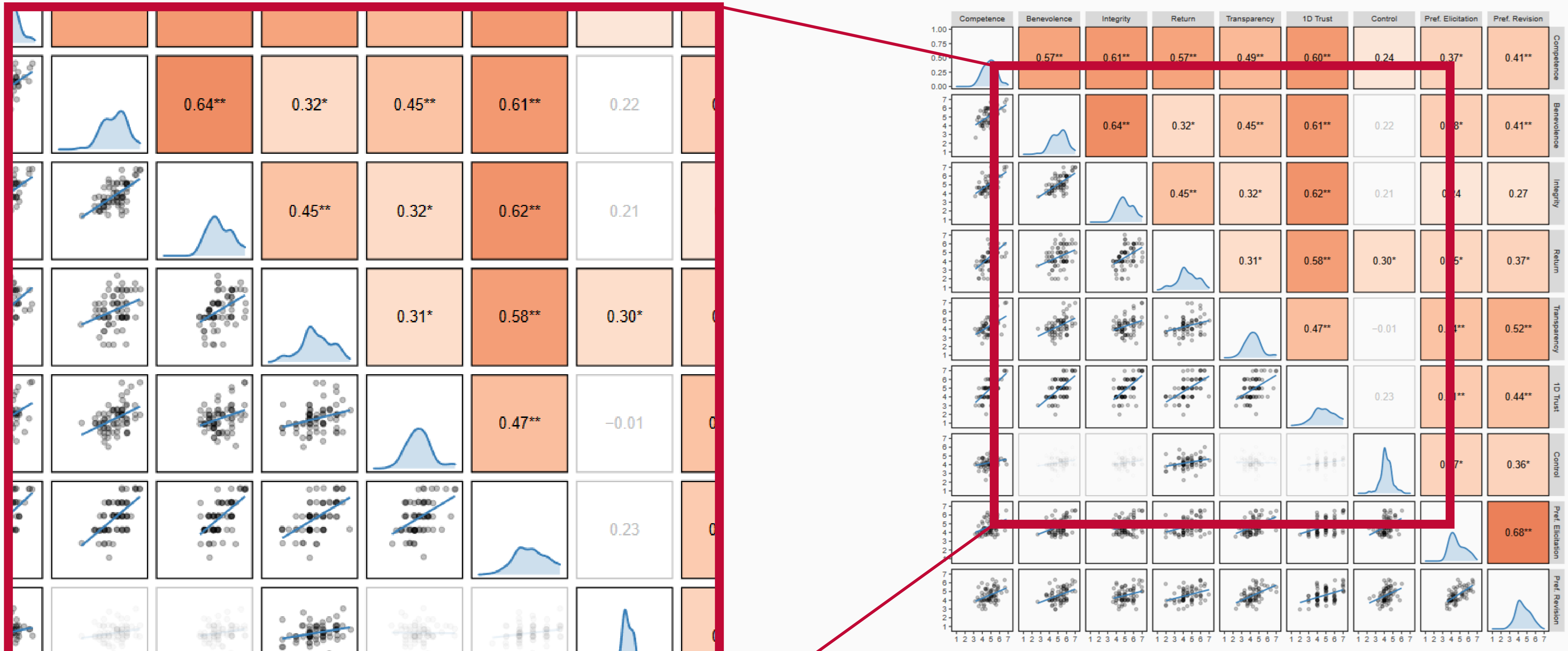
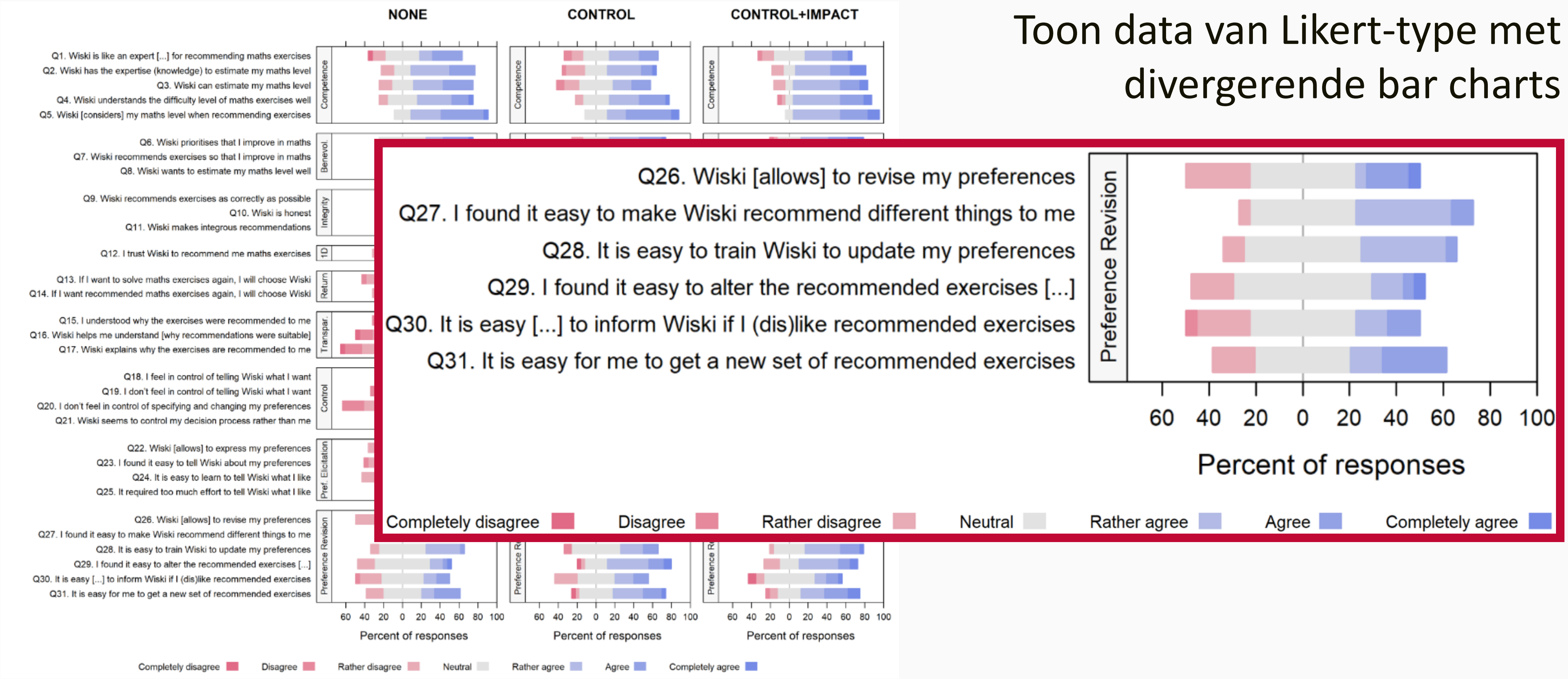


Figure 9: Relations between trust-related and control-related constructs. Lower triangle: dot plots with fitted regression lines. Diagonal: density plot of constructs. Upper triangle: correlations colour-coded by value ($^*p < 0.01$, $^{**}p < 0.001$). Non-significant relations ($p \geq 0.05$) are greyed out.

Jeroen Ooge, Leen Dereu, and Katrien Verbert. 2023. Steering Recommendations and Visualising Its Impact: Effects on Adolescents' Trust in E-Learning Platforms. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (IUI '23), 156–170. https://doi.org/10.1145/3581641.3584046

Tip 5: Toon niet-geaggregeerde data



Toon data van Likert-type met divergerende bar charts

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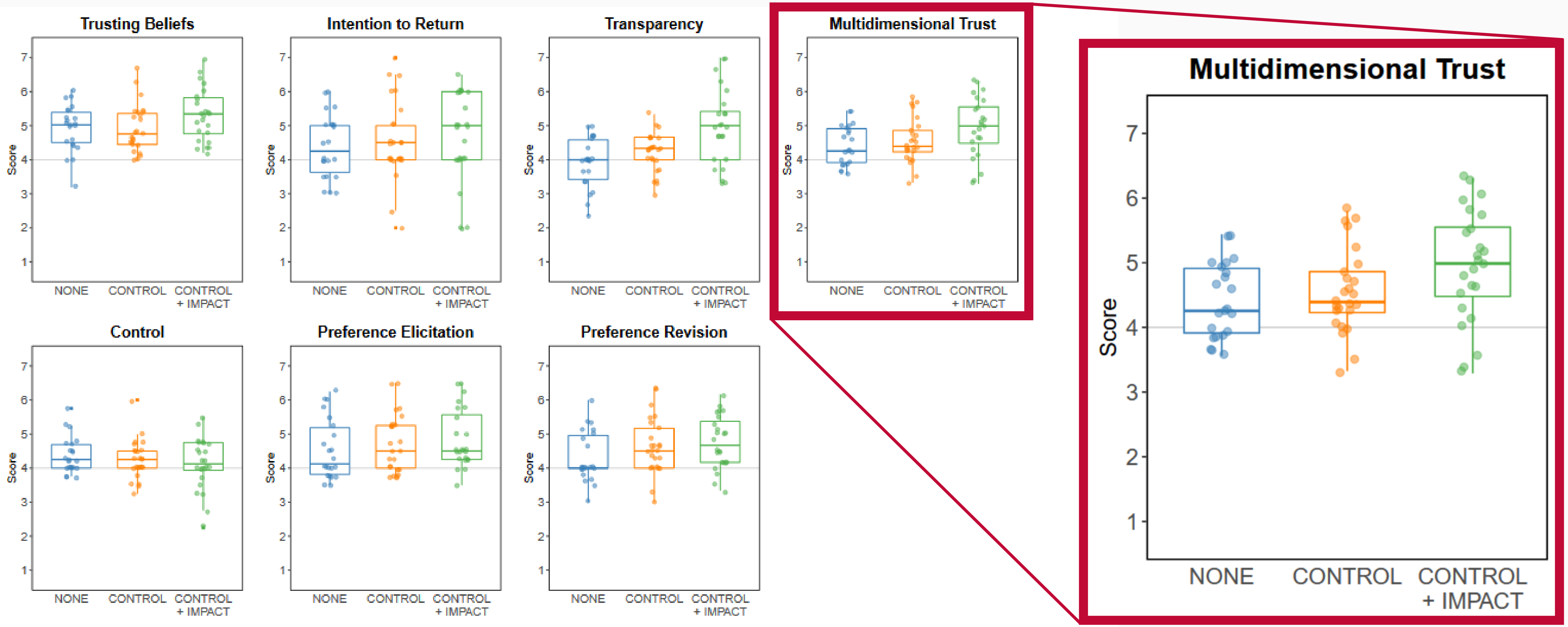
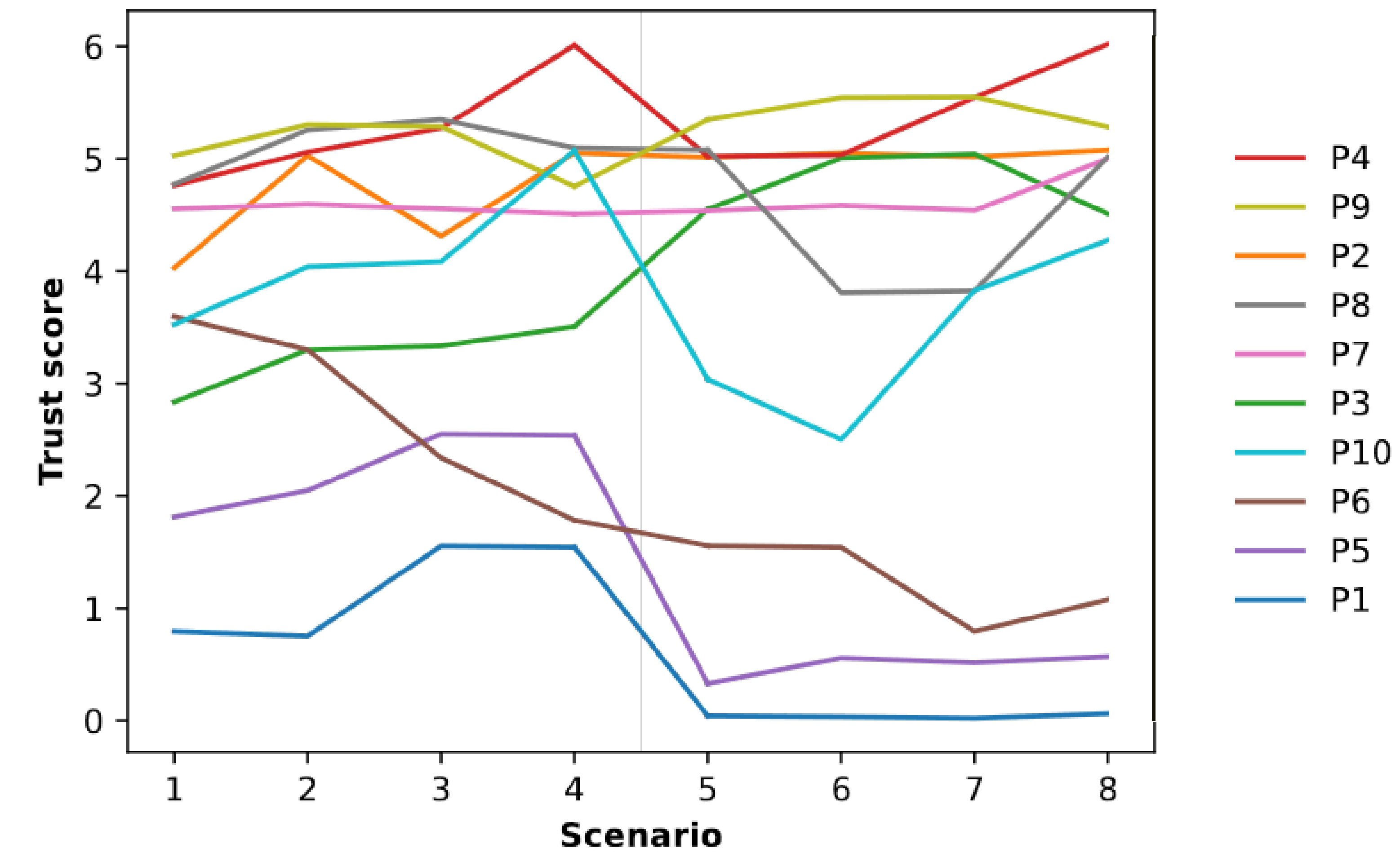


Figure 8: Box plots of the responses to the questionnaire in Table 2 for each research group. For visual clarity, the overlaying dot plots are slightly jittered horizontally and vertically.

Jeroen Ooge, Leen Dereu, and Katrien Verbert. 2023. Steering Recommendations and Visualising Its Impact: Effects on Adolescents’ Trust in E-Learning Platforms. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (IUI ’23), 156–170. https://doi.org/10.1145/3581641.3584046
Nick Desbarats. 2021. I’ve Stopped Using Box Plots. Should You? https://nightingaledvs.com/ive-stopped-using-box-plots-should-you/

Tip 6: Verrijk visualisaties betekenisvol



Welke lijn is wie?
Info scenarios?
Info deelnemers?

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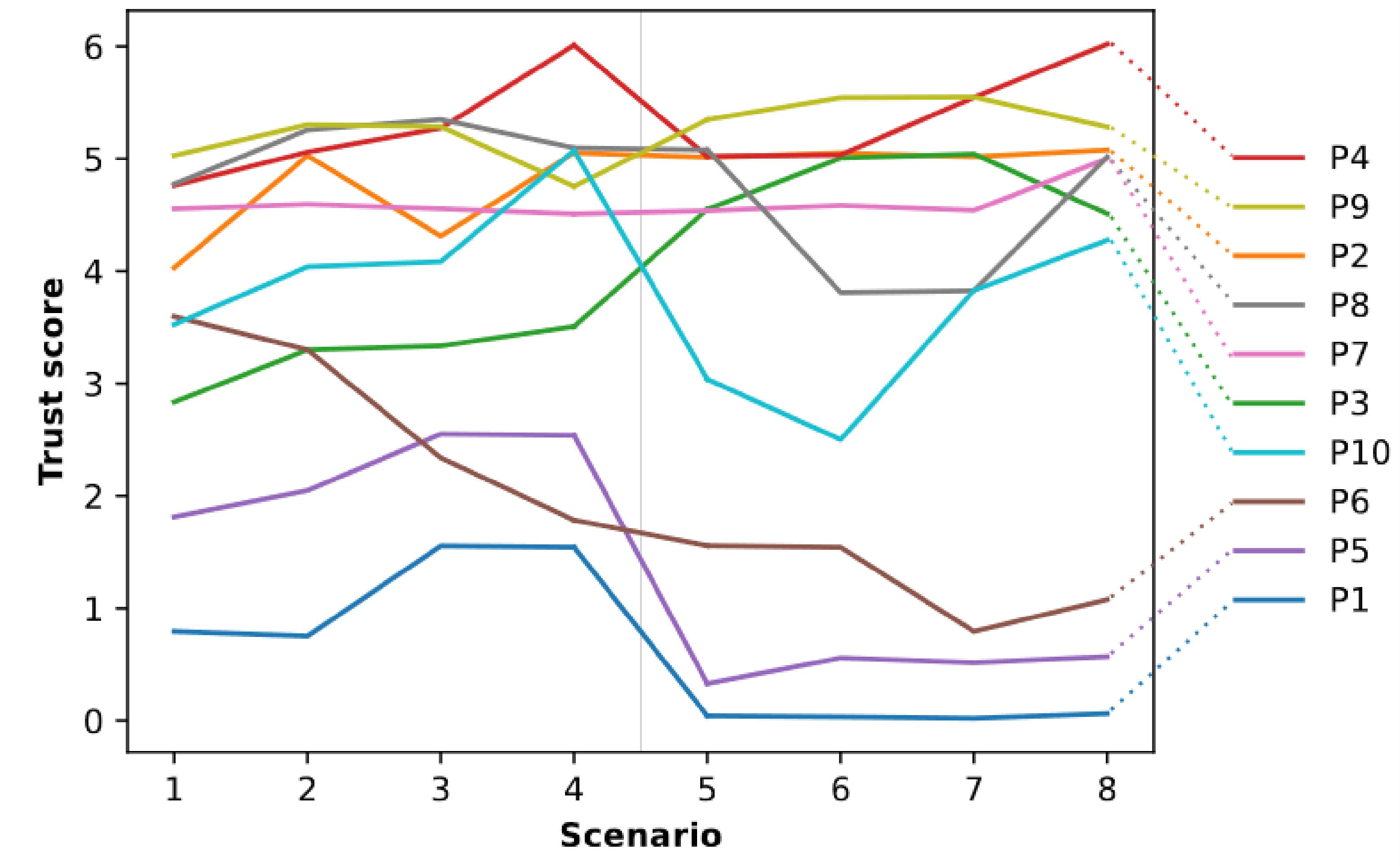

✅ Welke lijn is wie?
Info scenarios?
Info deelnemers?

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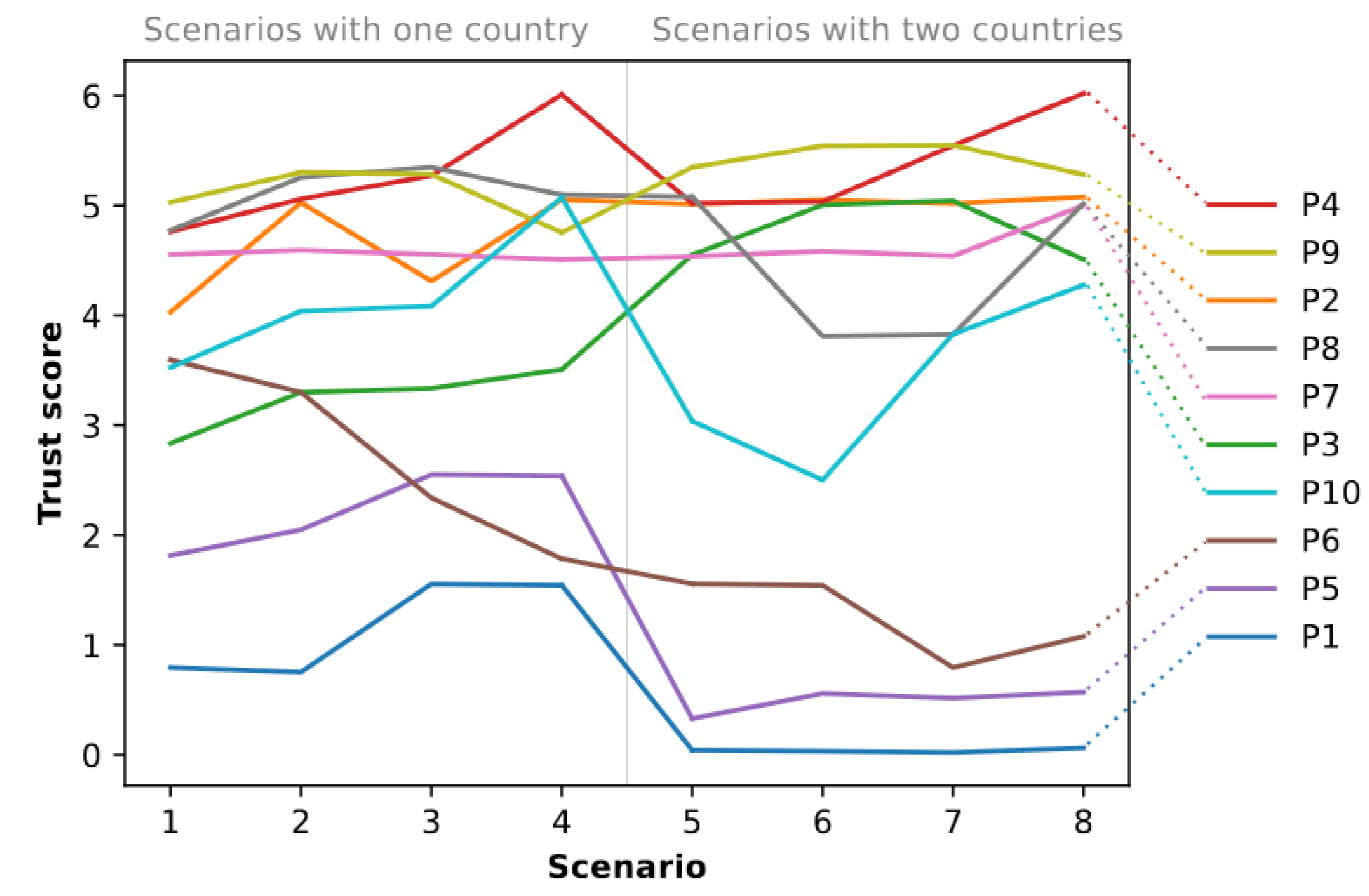

✅ Welke lijn is wie?
✅ Info scenarios?
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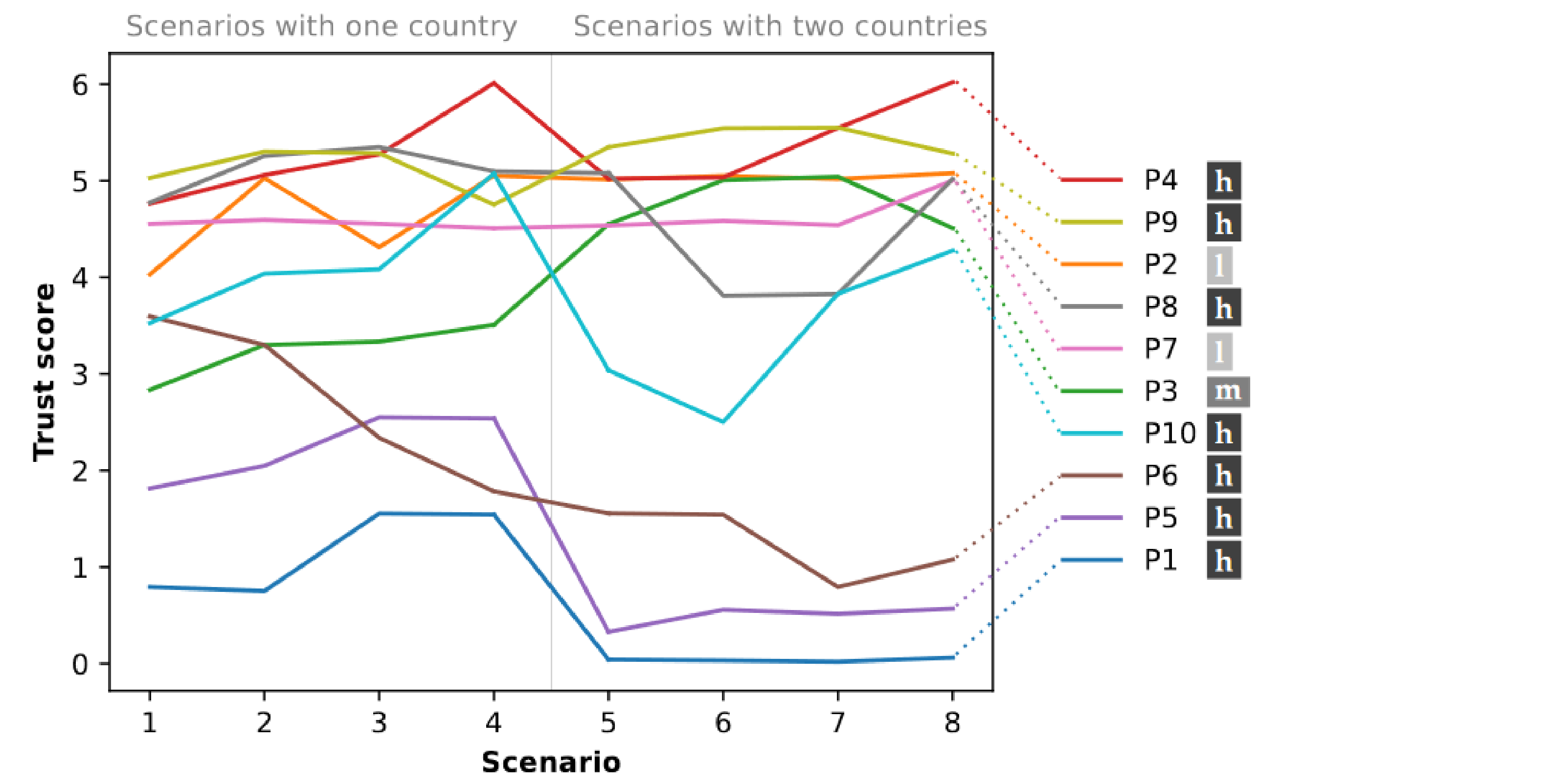

Figure 4. Participants' trust in the prediction model over eight scenarios. Scenarios 1–4 showed data for one country; Scenarios 5–8 showed data for two countries. Lines are slightly jittered for clarity. The legend includes the level of experience with predictive regression (l low, m medium, h high).

- ✅ Welke lijn is wie?
- ✅ Info scenarios?
- ✅ Info deelnemers?

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https://doi.org/10.3390/agriculture12071024

Hoorcollege 4

Visualisaties in rapporten
Interactieve visualisaties

1. Vis in rapporten
2. Interactieve vis
3. Tentamen

Jippie, bewegende vis!

Universiteit Utrecht

Waarom interactie?

Schaal
Veel datapunten of dimensies

Storytelling
Visueel verhaal vertellen

Exploratie
Data verkennen zonder verhaal

Betrokkenheid
Plezier en interesse wekken

Slide source: Michael Porath

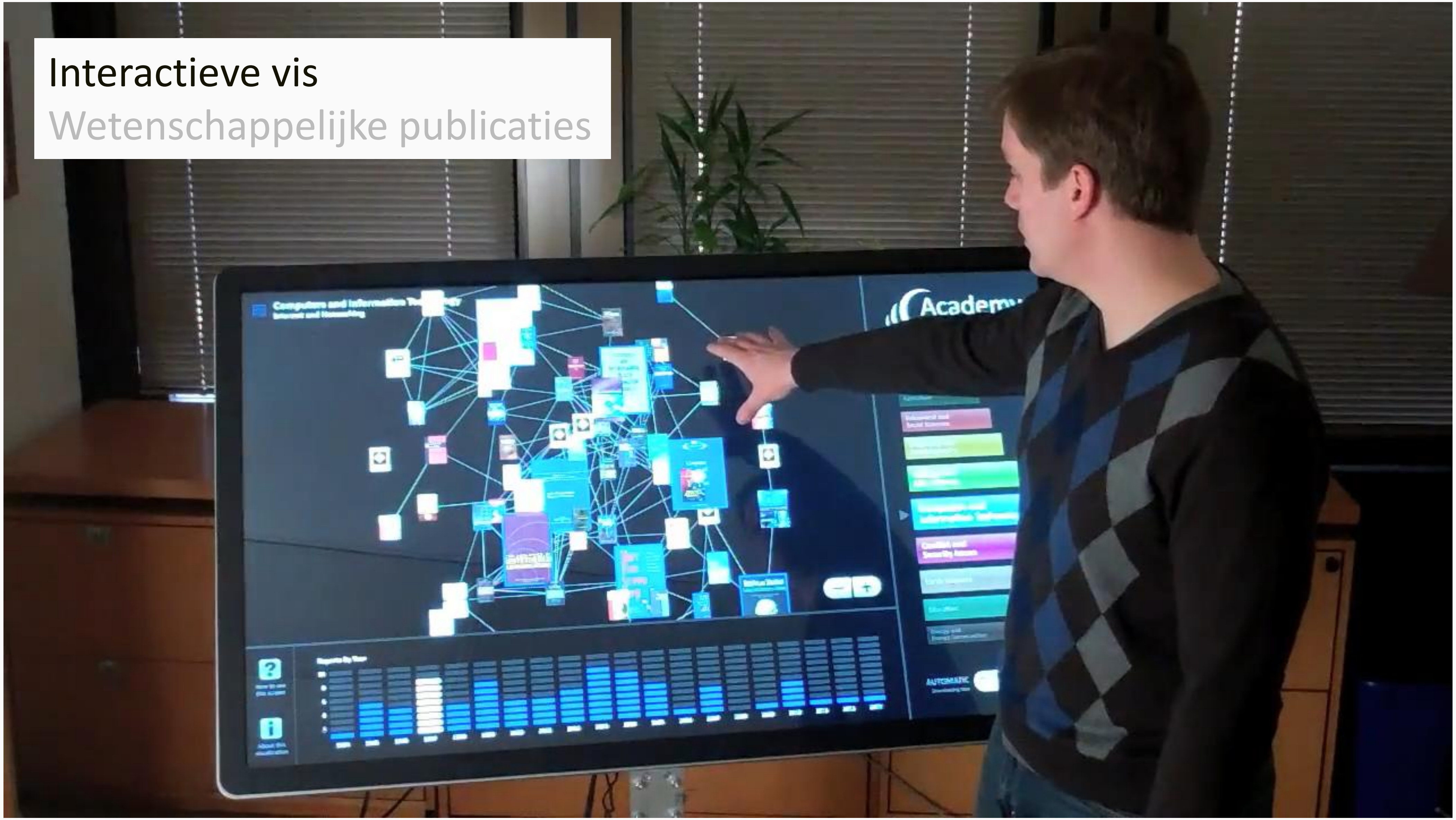
Interactieve vis

Openbaar vervoer in Singapore

Touching Bus Rides. https://www.youtube.com/watch?v=wQpTM7ASc-w

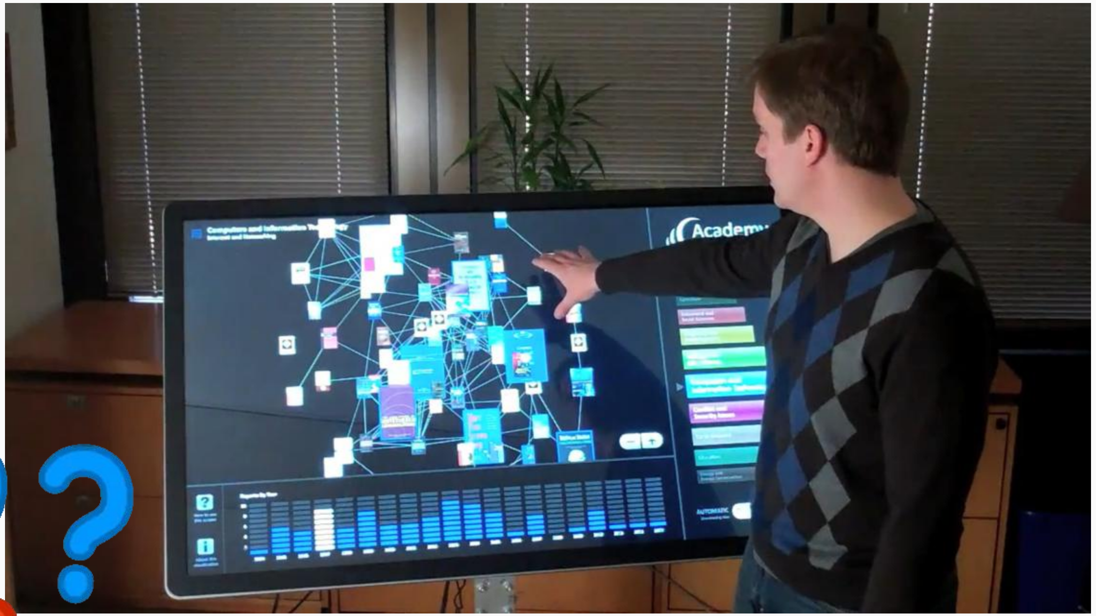
Interactieve vis

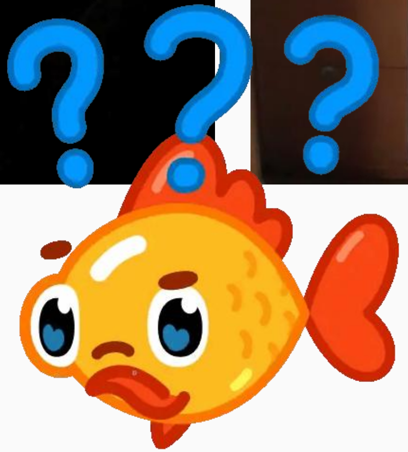
Wetenschappelijke publicaties



The Making of AcademyScope. https://www.youtube.com/watch?v=pdqKBna1Fos

Interactievormen voor vis





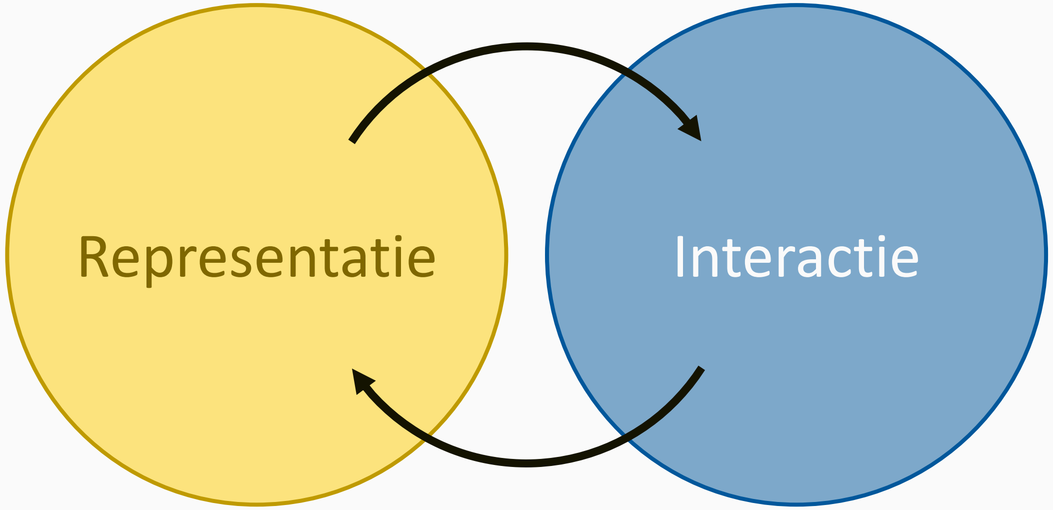
Welke interacties zag je?

Interactievormen voor vis

- Exploreren
- Connecteren
- Filteren
- Configureren
- Encoderen
- Samenvatten/detailleren
- Selecteren

Welke interactievormen je kiest hangt af van:

- het doel van gebruikers
- de inzichten die je wilt ondersteunen



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Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Interactievormen voor vis

Statische vis focust meestal op 1 centrale boodschap

Exploreren

Connecteren

Filteren

Configureren

Encoderen

Samenvatten/detailleren

Selecteren

Communiceren
Verklarend

Analyseren
Exploratief

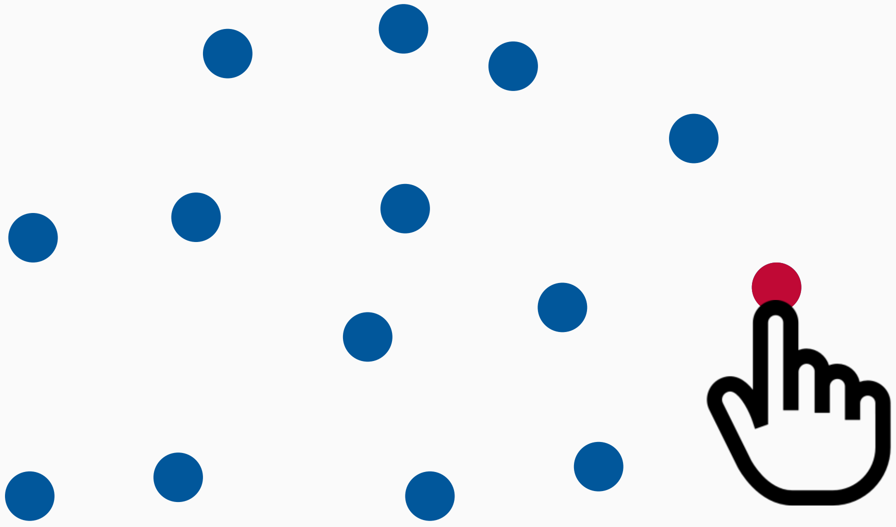
Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Selecteren

Duid interessante datapunten aan

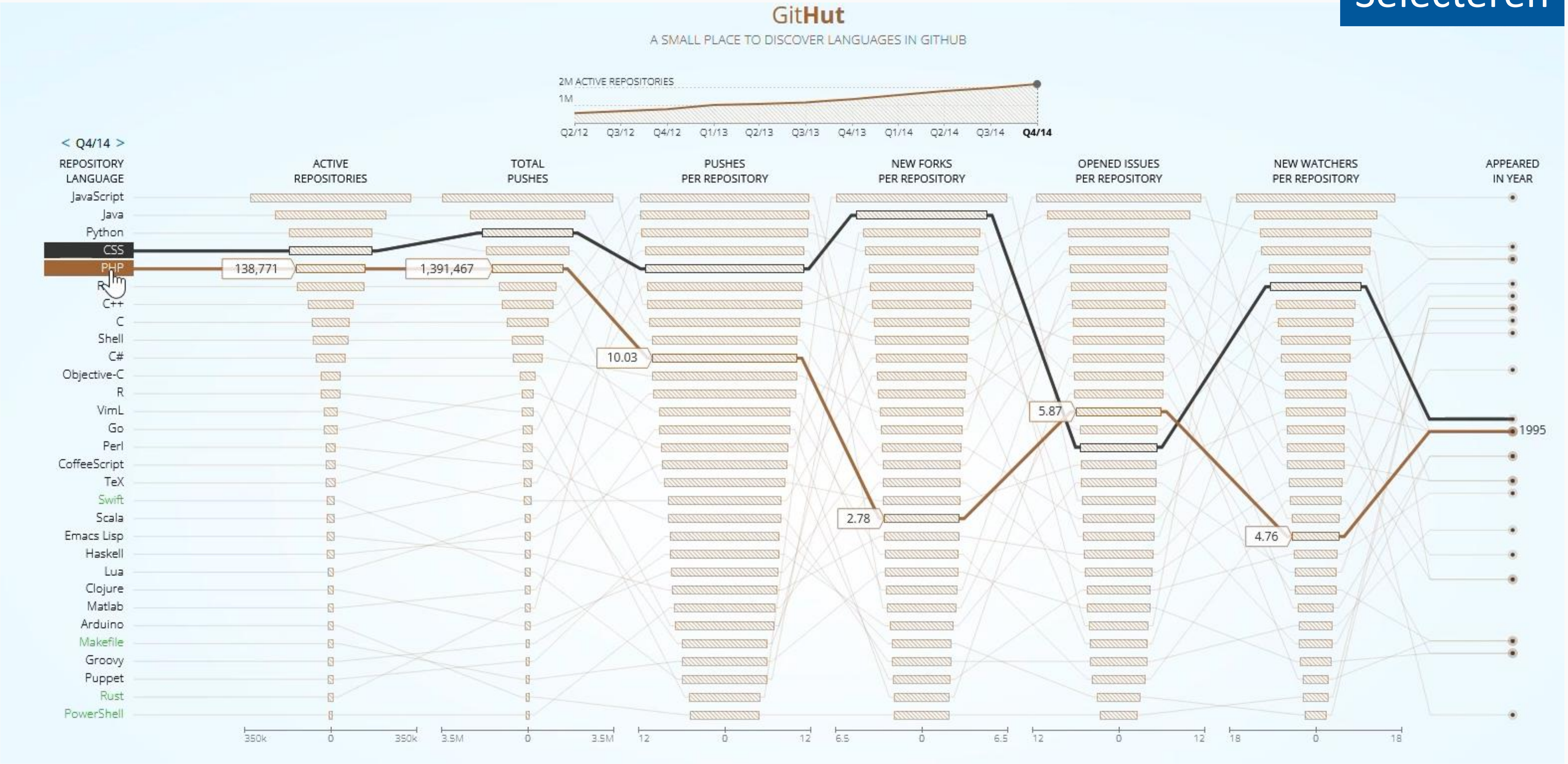
Typisch een eerste stap voor verdere interacties

Voorbeeld: traceer een datapunt



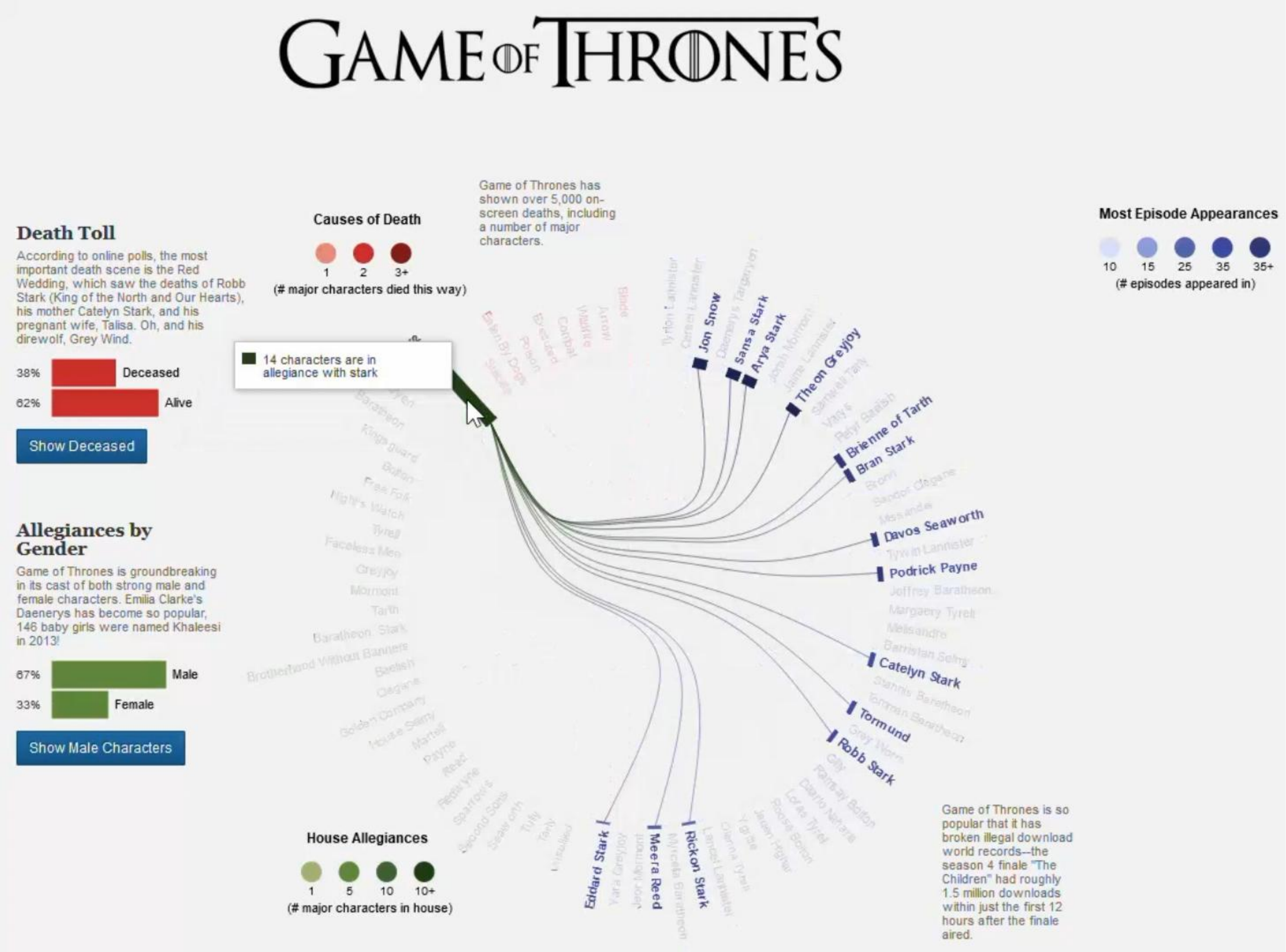
Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Selecteren



GitHut, A small place to discover languages in GitHub. https://githut.info

Selecteren



Visualizing Game of Thrones. https://github.com/josselyntsai/thronesviz.github.io
http://chenhui.li/courses/beadata2023/thronesviz

Samenvatten/detailleren

Toon meer of minder details

Voorbeeld: tooltips

“Overview first, zoom and filter, then details-on-demand
Overview first, zoom and filter, then details-on-demand
Overview first, zoom and filter, then details-on-demand
Overview first, zoom and filter, then details-on-demand”

Visual Information-Seeking Mantra. Ben Schneiderman, 2003. https://doi.org/10.1016/B978-155860915-0/50046-9

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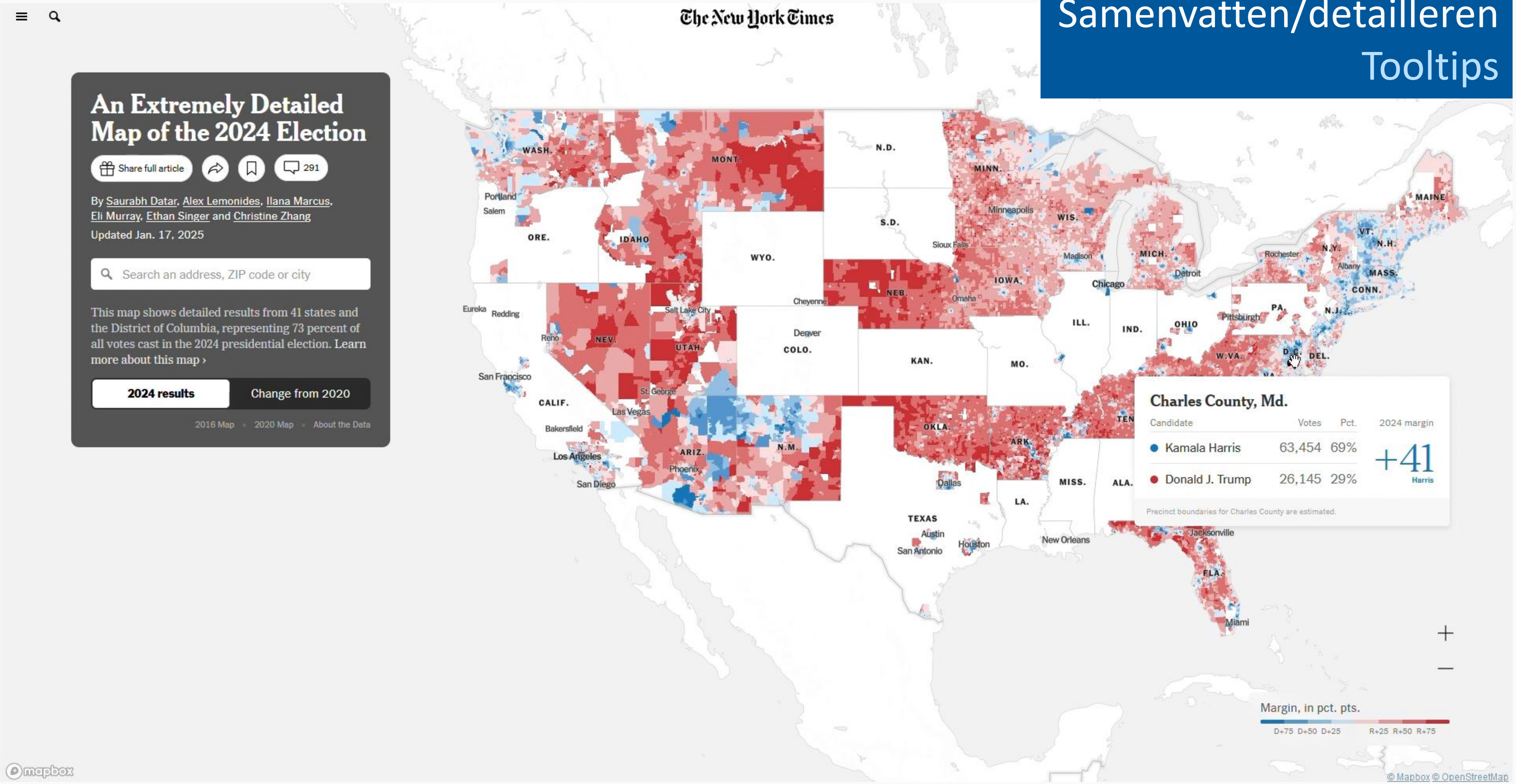
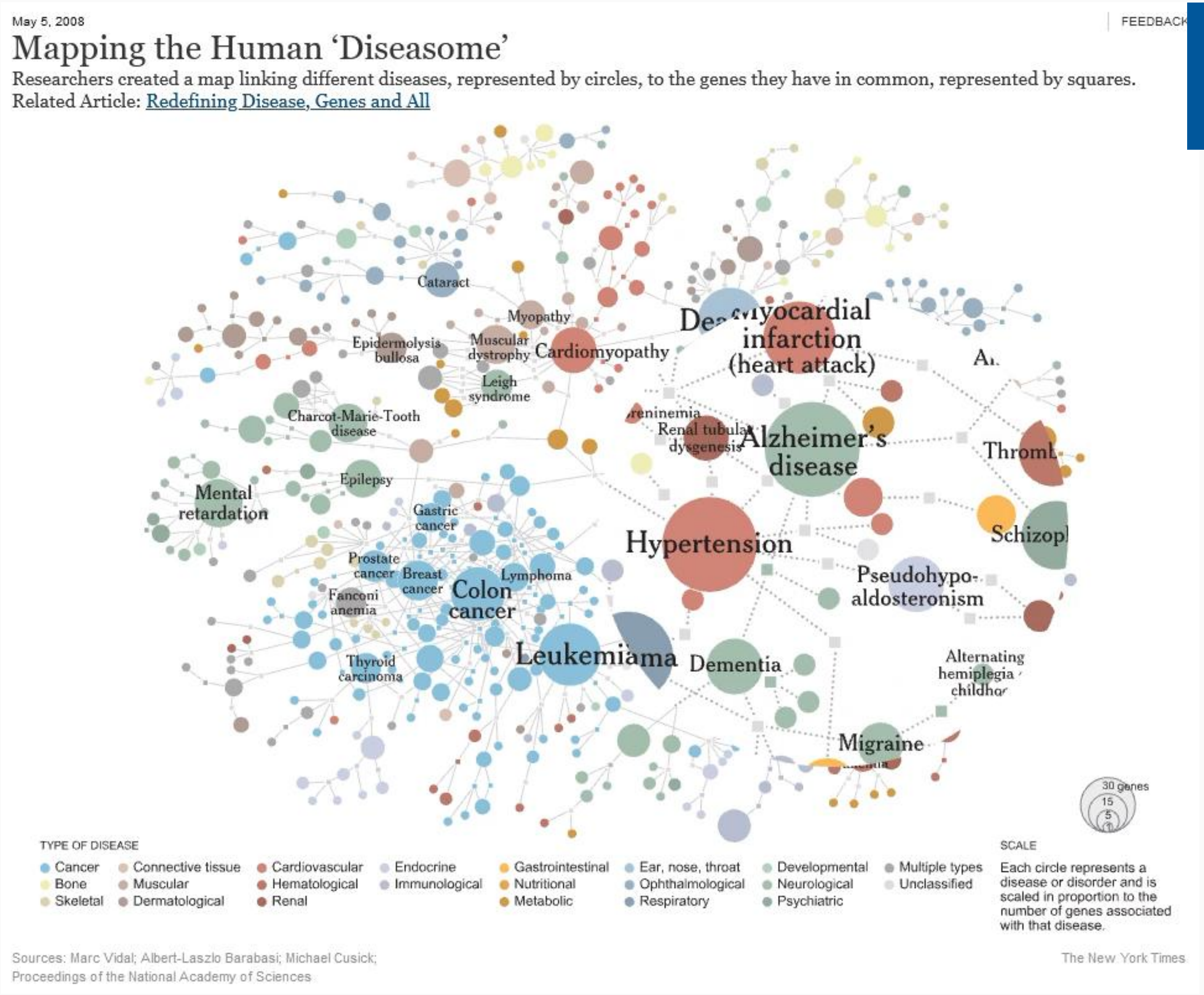
Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Samenvatten/detailleren
Tooltips



An Extremely Detailed Map of the 2024 Election. https://www.nytimes.com/interactive/2025/us/elections/2024-election-map-precinct-results.html

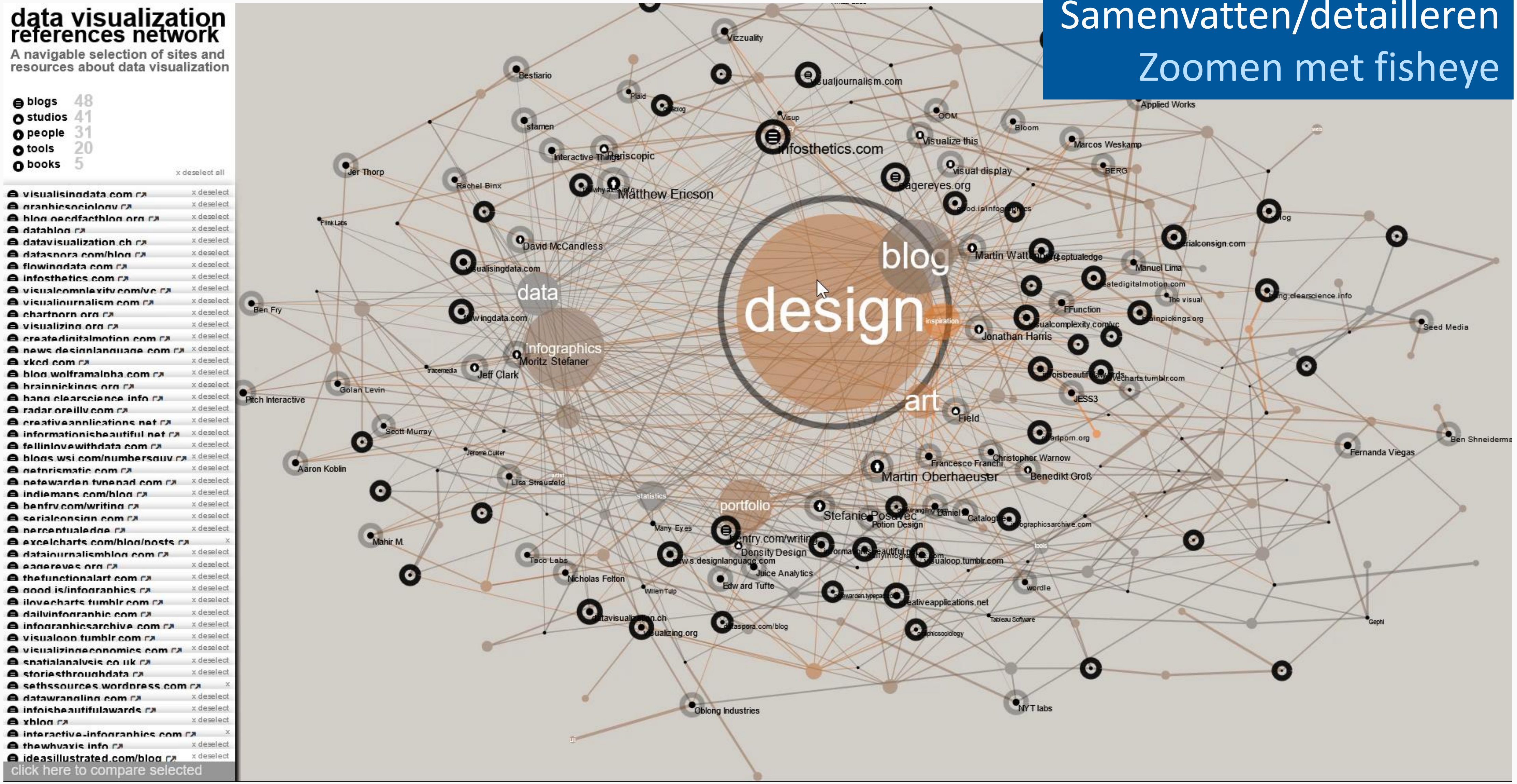
Samenvatten/detailleren
Klassiek zoomen



www.nytimes.com/interactive/2008/05/05/science/20080506_DISEASE.html

Samenvatten/detailleren

Zoomen met fisheye



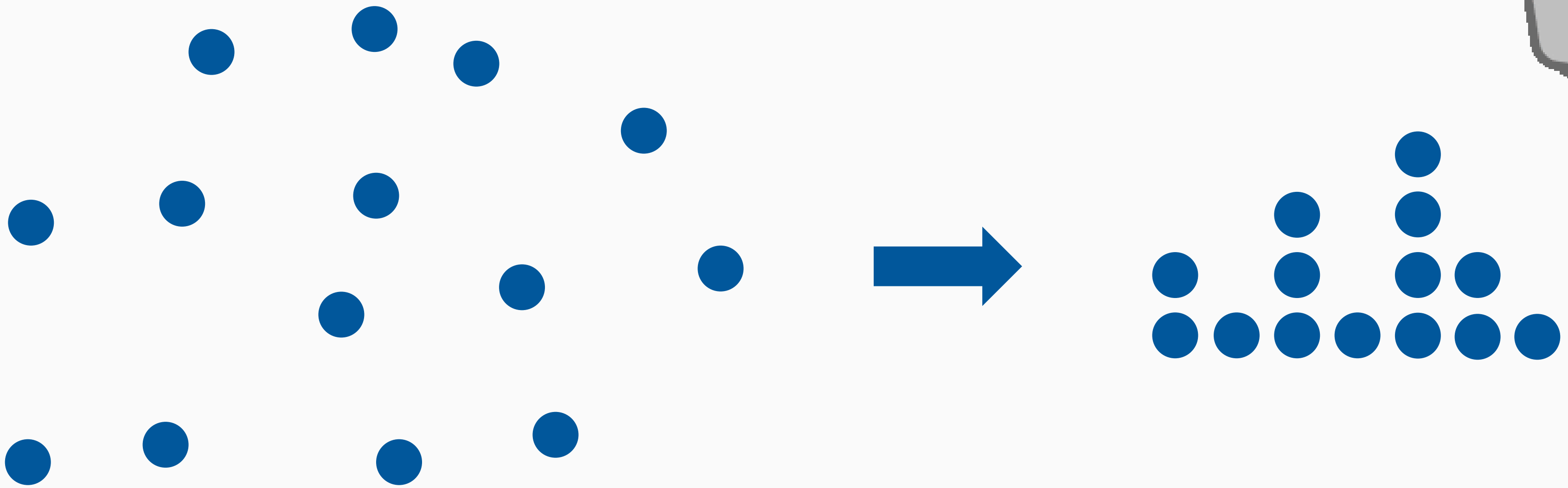
Data visualization references network. https://moebio.com/datavisnetwork

Encoderen

Toon een andere representatie

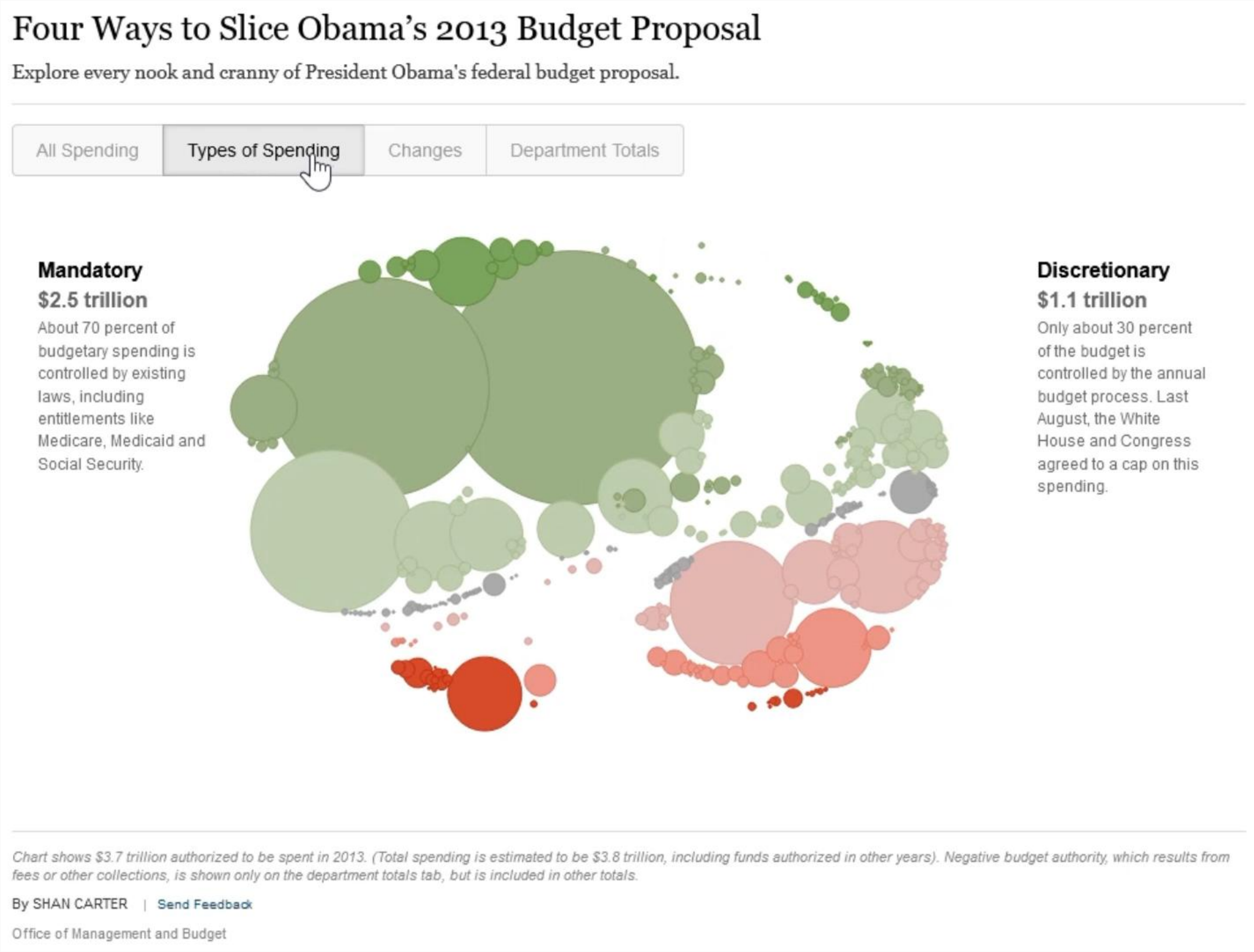
Verander de encodering van datapunten (kleur, grootte, vorm…)

Voorbeeld: verander een scatterplot in een dot plot



Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Encoderen



Four Ways to Slice Obama's 2013 Budget Proposal. https://nytimes.com/interactive/2012/02/13/us/politics/2013-budget-proposal-graphic.html

Configureren

Verander de positie van datapunten

Voorbeelden: kolommen sorteren, datapunten vrij rondbewegen, attributen op assen wijzigen…

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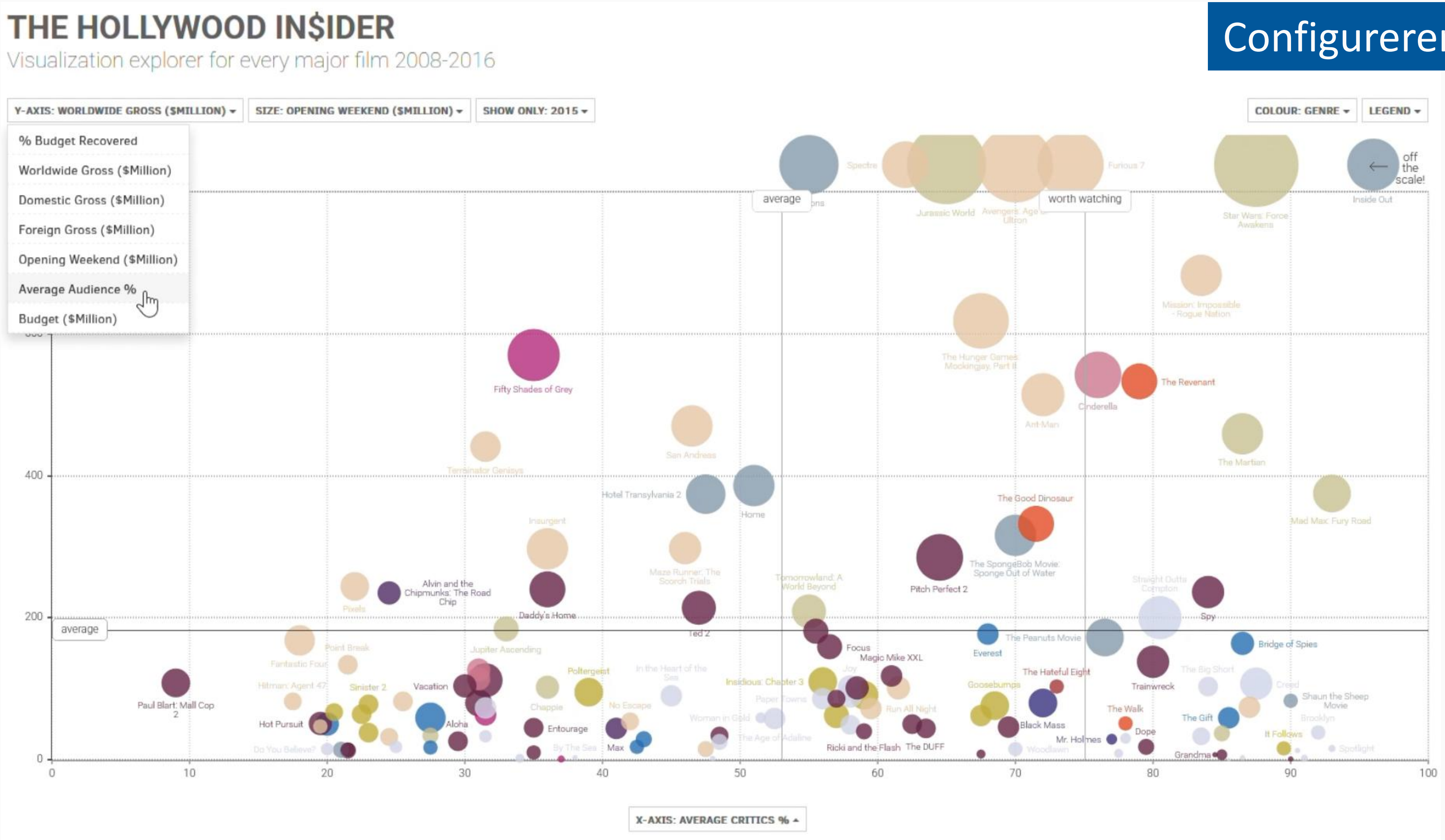
Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Configureren

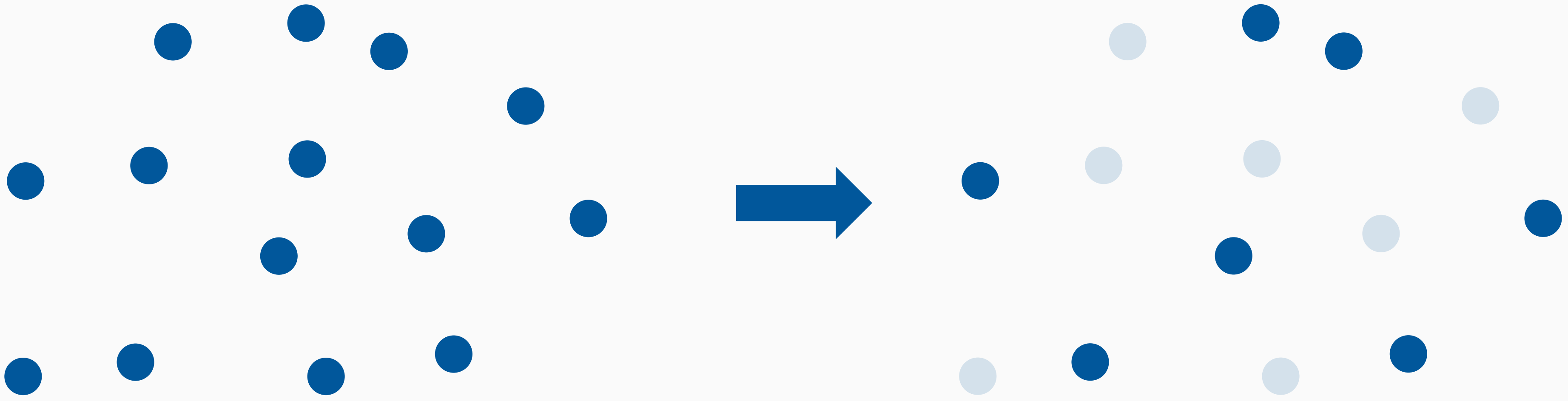


The Hollywood In$ider: Visualization explorer for every major film 2008-2016. https://informationisbeautiful.net/visualizations/the-hollywood-insider

Filteren

Toon datapunten onder gekozen voorwaarden

Voorbeeld: verberg datapunten met waardes buiten een gegeven interval

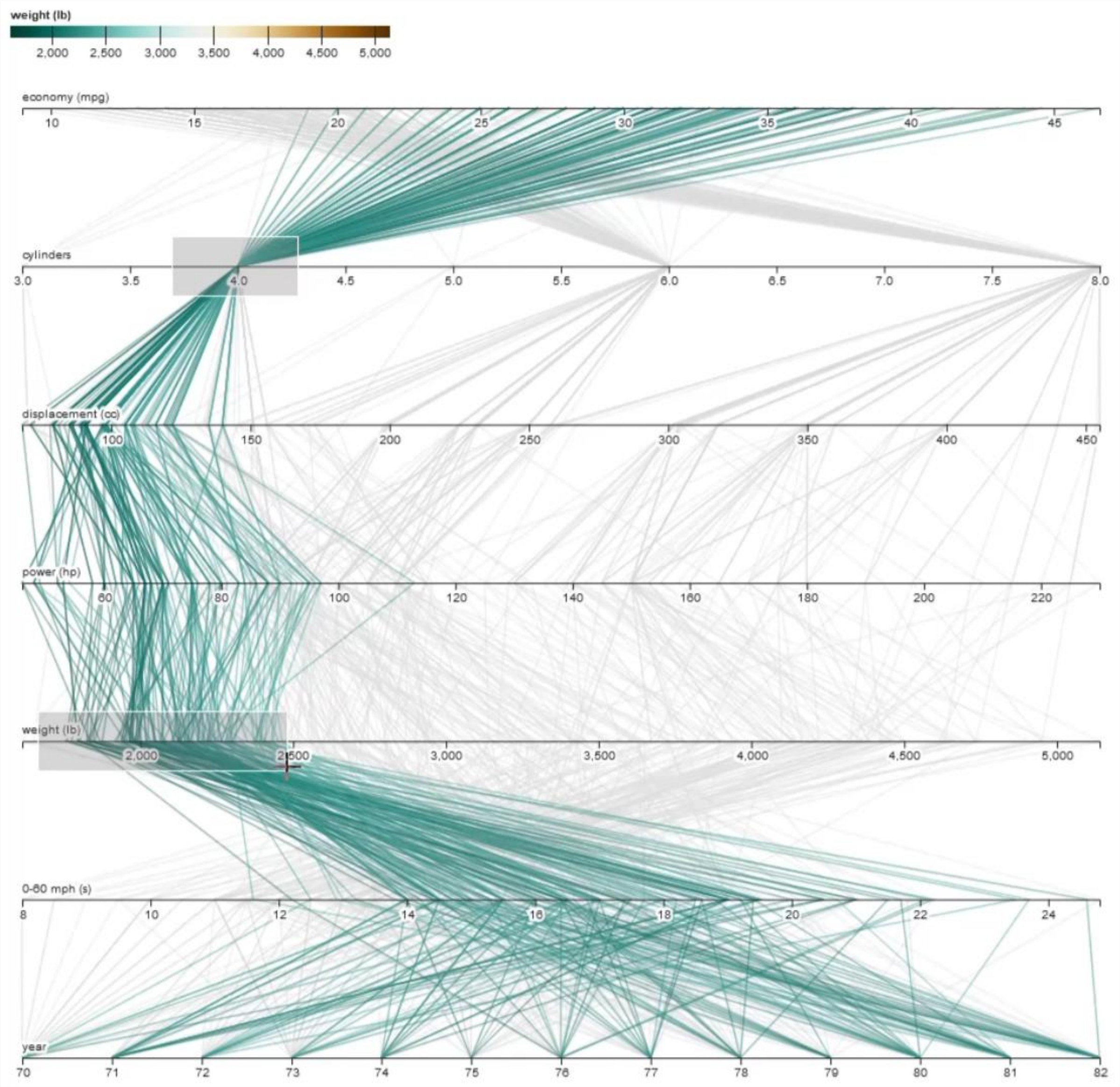


Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Filteren Dropdown

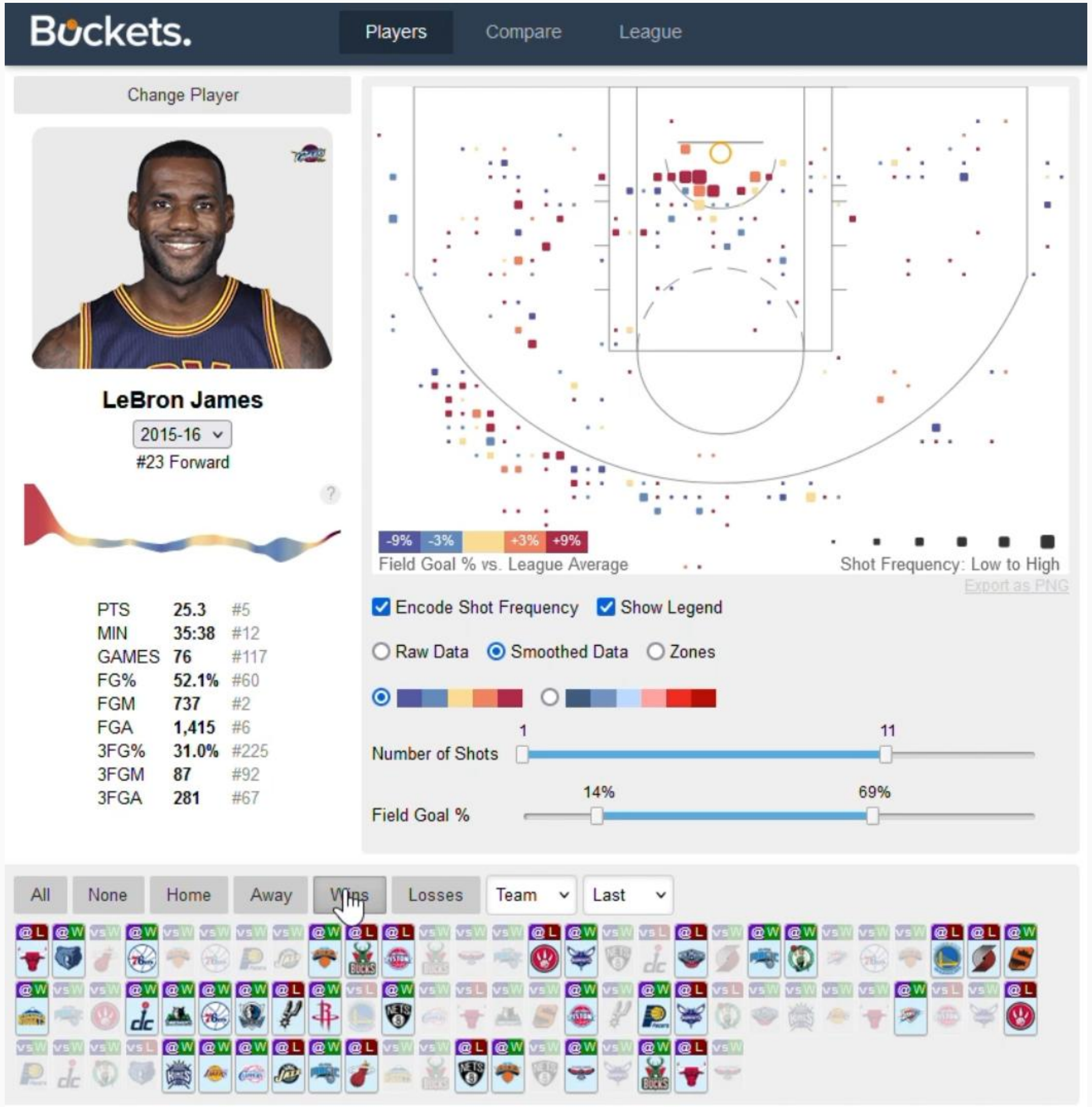
Jeroen Ooge and Katrien Verbert. 2022. Visually Explaining Uncertain Price Predictions in Agrifood: A User-Centred Case-Study. *Agriculture* 12, 7: 1024. https://doi.org/10.3390/agriculture12071024

Filteren
Brushing



https://observablehq.com/@d3/brushable-parallel-coordinates

Filteren
Sliders en knoppen

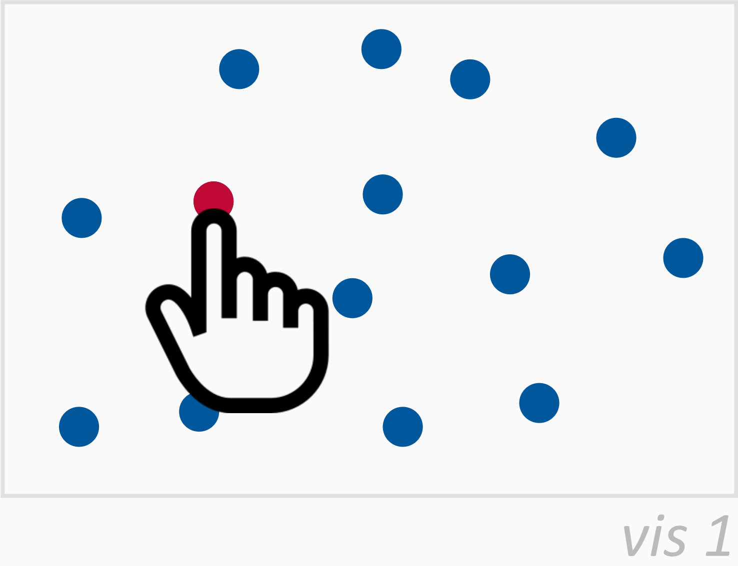


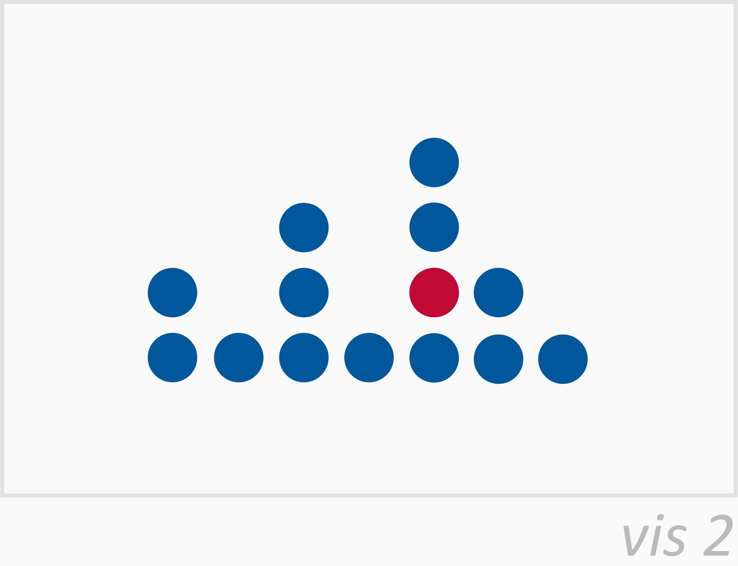
Buckets: NBA Shot Visualization. https://buckets.peterbeshai.com

Connecteren

Toon gerelateerde datapunten en relaties

Voorbeeld: highlight overeenkomstige datapunten in verschillende visualisaties





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Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

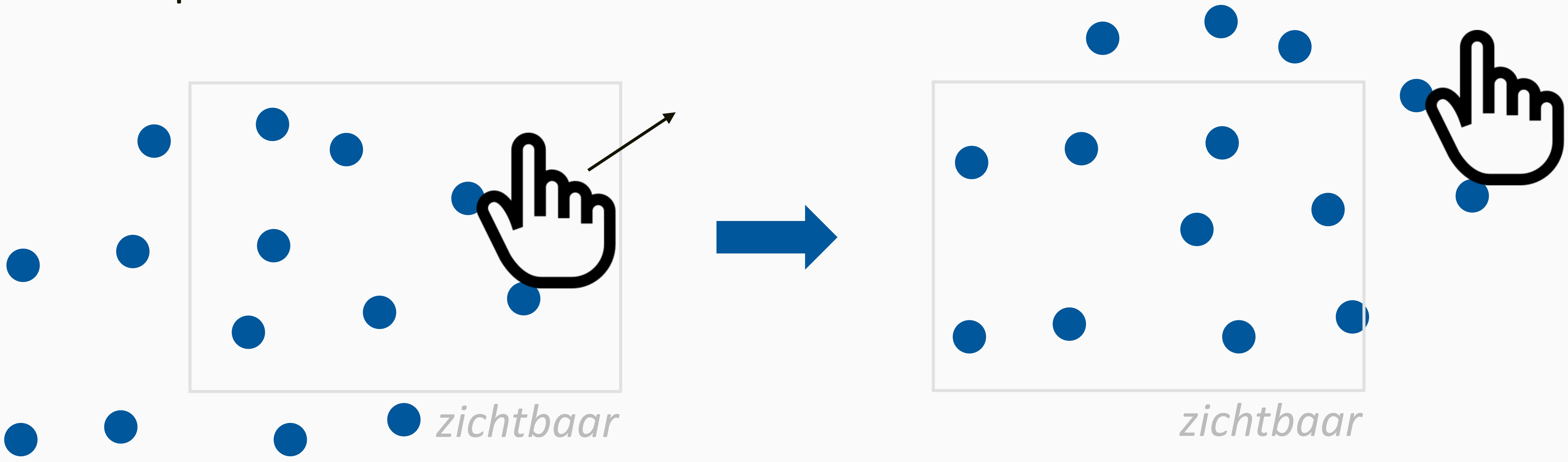
Connecteren

Buckets: NBA Shot Visualization. https://buckets.peterbeshai.com

Exploreren

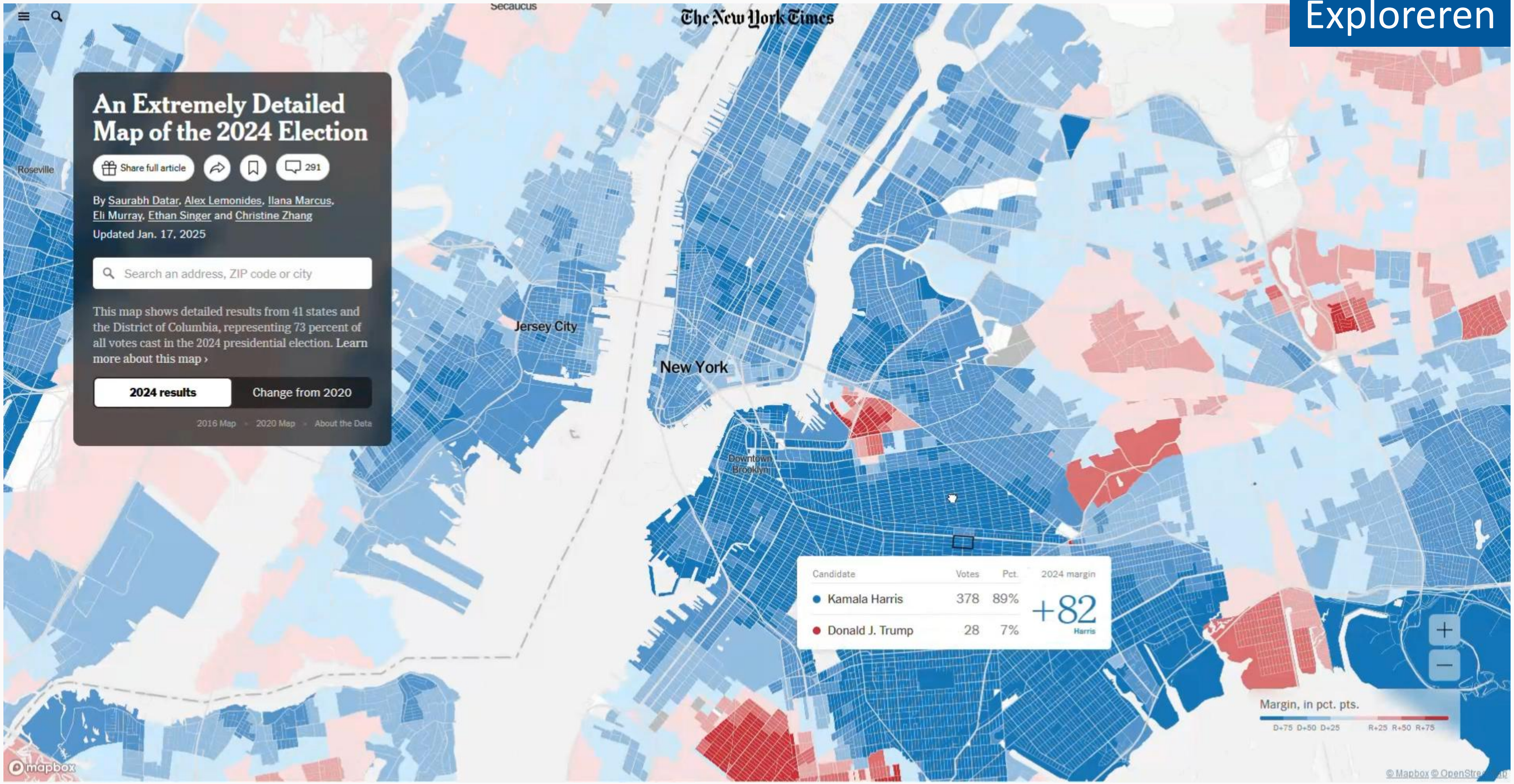
Toon andere datapunten

Voorbeeld: pannen



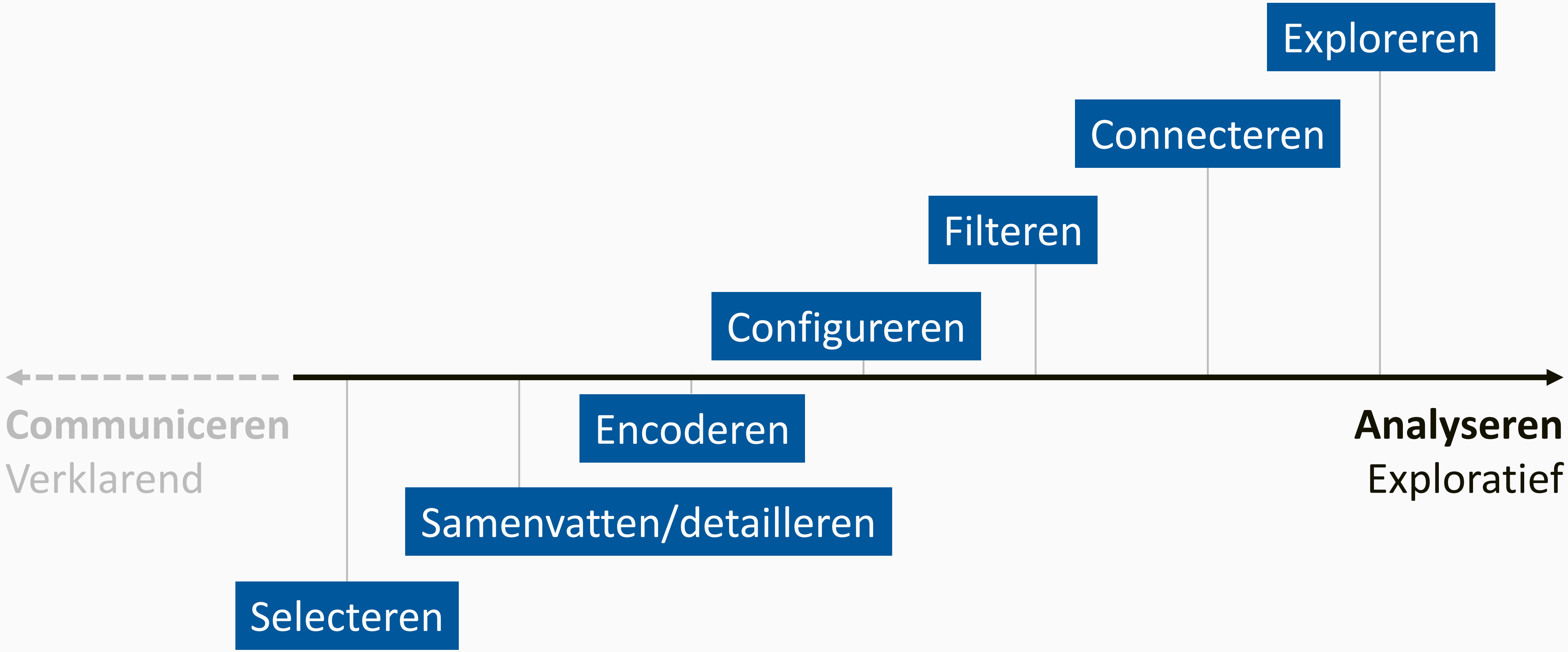
Ji Soo Yi, Youn ah Kang, John Stasko, and J.A. Jacko. 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics* 13, 6: 1224–1231. https://doi.org/10.1109/TVCG.2007.70515

Exploreren



An Extremely Detailed Map of the 2024 Election. https://www.nytimes.com/interactive/2025/us/elections/2024-election-map-precinct-results.html

Interactievormen voor vis



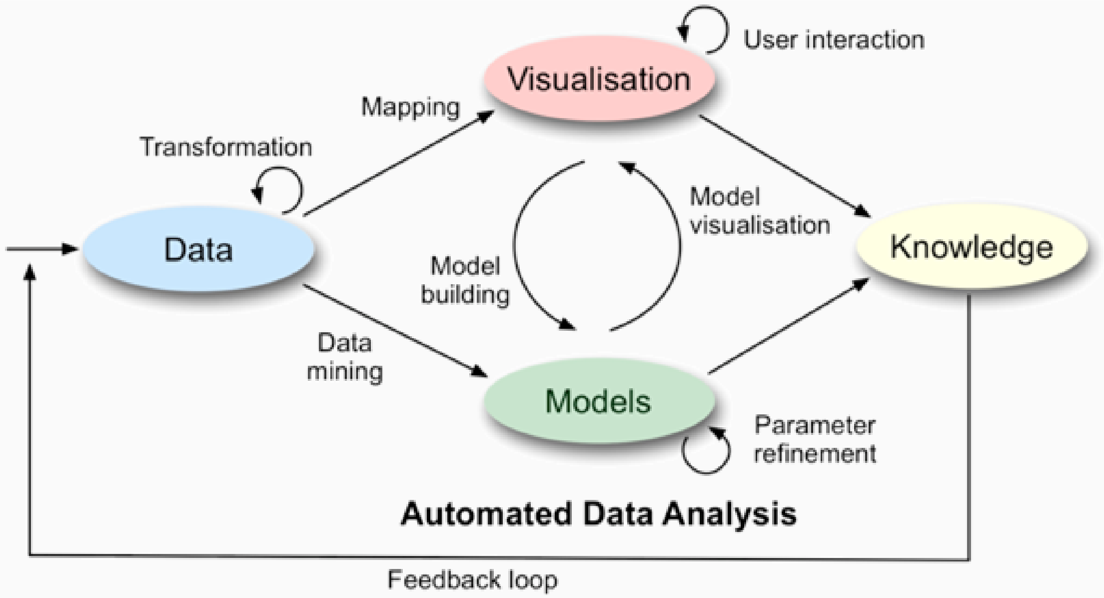
Visual analytics

- Exploreren
- Connecteren
- Filteren
- Configureren
- Encoderen
- Samenvatten/detailleren
- Selecteren

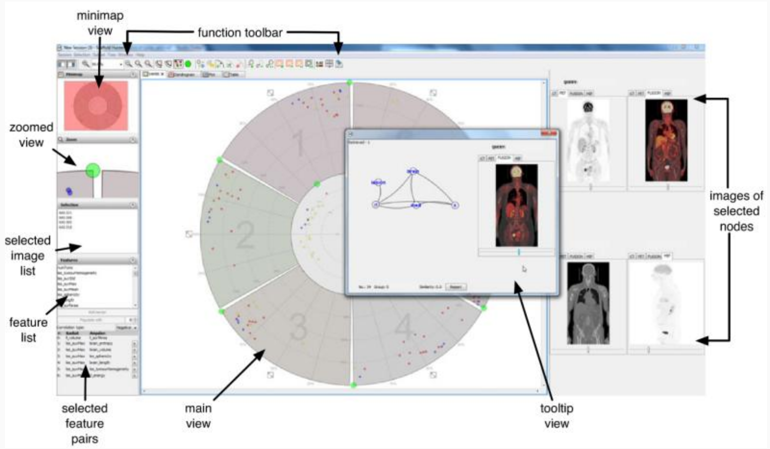
Exploratief visueel analyseren

+ grote hoeveelheden data

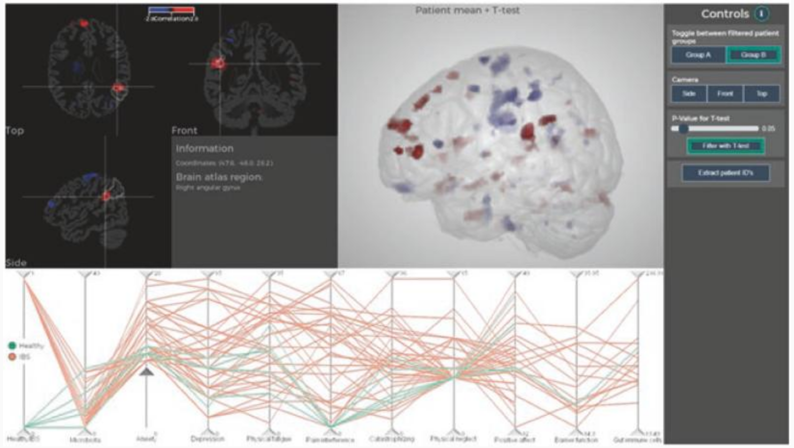
+ ondersteuning door statistiek en AI



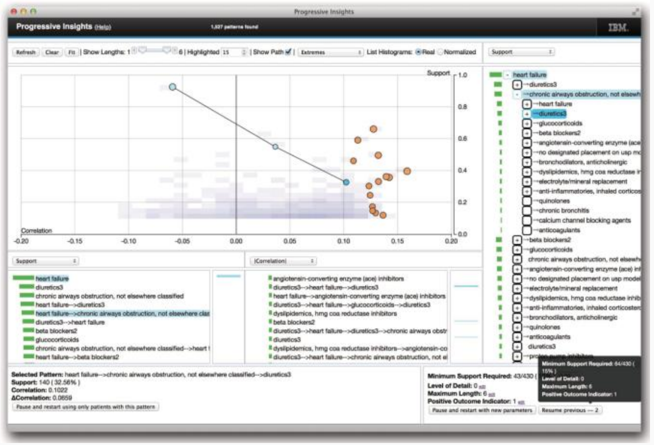
Daniel A. Keim, Florian Mansmann, Jörn Schneidewind, Jim Thomas, and Hartmut Ziegler. 2008. Visual Analytics: Scope and Challenges. In *Visual Data Mining*. Springer Berlin Heidelberg, Berlin, Heidelberg, 76–90. https://doi.org/10.1007/978-3-540-71080-6_6



Samenvatten/detailleren

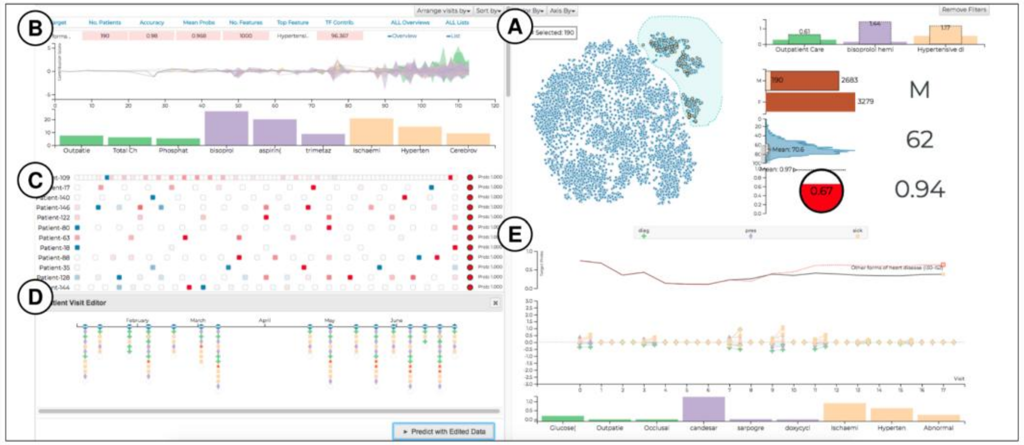


Filteren



Configureren

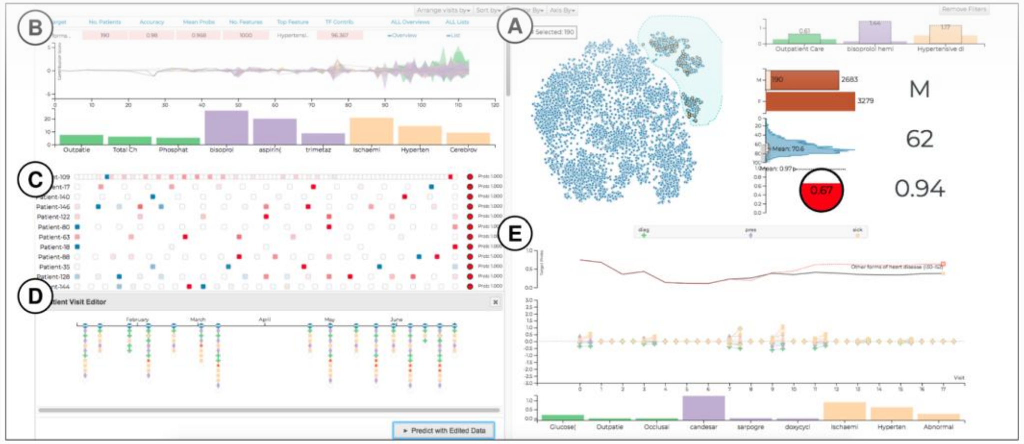
Encoderen



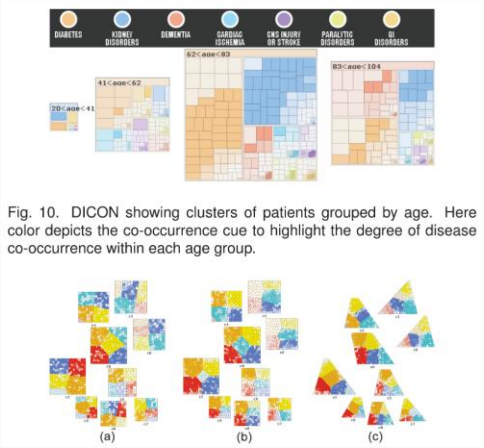
Selecteren

Jeroen Ooge, Gregor Stiglic, and Katrien Verbert. 2022. Explaining artificial intelligence with visual analytics in healthcare. *WIREs Data Mining and Knowledge Discovery* 12, 1: e1427. https://doi.org/10.1002/widm.1427

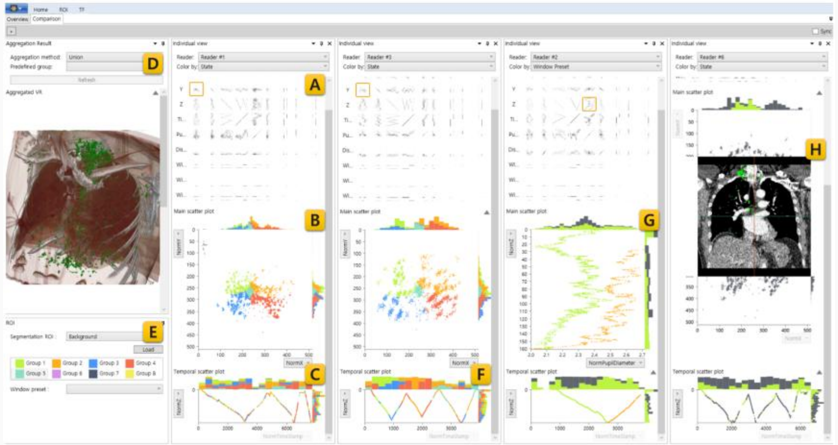
Encoderen



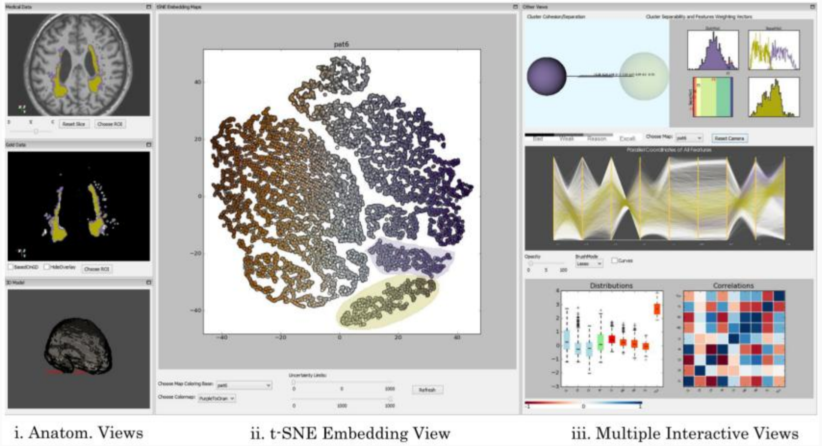
Selecteren



Connecteren



Exploreren



Selecteren + connecteren

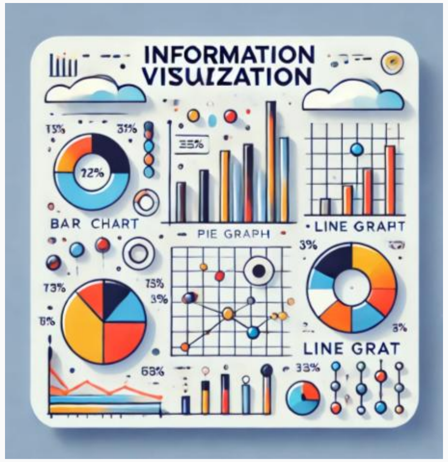
Jeroen Ooge, Gregor Stiglic, and Katrien Verbert. 2022. Explaining artificial intelligence with visual analytics in healthcare. *WIREs Data Mining and Knowledge Discovery* 12, 1: e1427. https://doi.org/10.1002/widm.1427

Hoorcollege 4

Visualisaties in rapporten
Interactieve visualisaties

1. Vis in rapporten
2. Interactieve vis
3. Tentamen

Te kennen leerstof



Hoorcollege 1
Algemene principes
Data-inkt ratio
Klassieke vis-types
~~Namen en jaartallen~~
~~Details over vis-tools~~

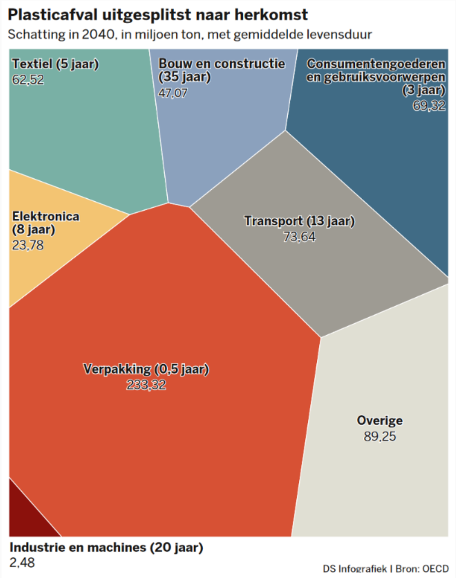
Hoorcollege 2
Genest model
Marks en channels
Visuele perceptie
Kleurgebruik

Hoorcollege 3
Types misleiding
~~Inleiding ggplot2~~

Hoorcollege 4
Vis-tips voor rapporten
Types interactie

Tips voor het tentamen

- Signaleer tijdig toetsvoorzieningen
- Breng 2-3 kleuren mee om te schetsen
- Antwoord concreet en gebruik gepaste vis-termen



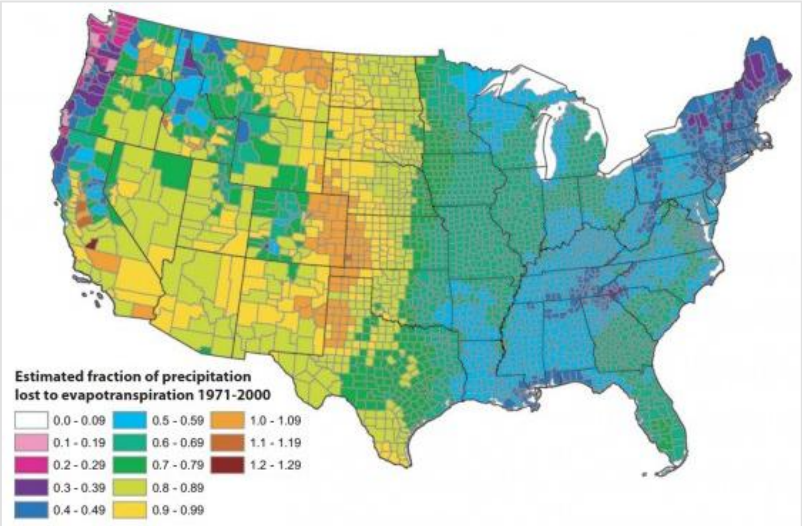
Noem 1 nadeel van de visuele encodering.

👎 Het is moeilijk te vergelijken.

👍 Grootte-aantallen worden geëncodeerd door het channel 'oppervlakte'. Positie met gelijke schaal is echter een effectiever channel om groottes te vergelijken. Een bar chart zou bijvoorbeeld effectiever zijn.

Tips voor het tentamen

- Signaleer tijdig toetsvoorzieningen
- Breng 2-3 kleuren mee om te schetsen
- Antwoord concreet en gebruik gepaste vis-termen



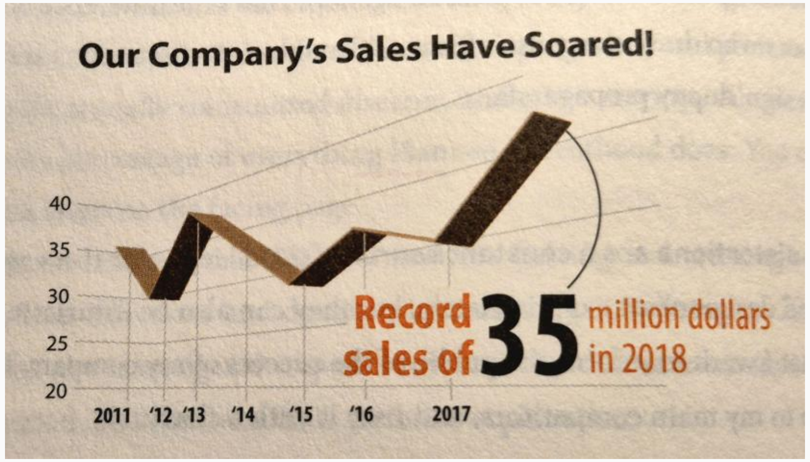
Bespreek het kleurgebruik.

👎 Te veel kleuren en niet goed.

👍 De kleuren encoderen aantallen, wat ordinale data is. Daarvoor is een sequentieel kleurpalet geschikt, bv. varieer de saturatie van wit (laag aantal) naar blauw (hoog aantal). Hier wordt echter een regenboogpalet gebruikt.

Tips voor het tentamen

- Signaleer tijdig toetsvoorzieningen
- Breng 2-3 kleuren mee om te schetsen
- Antwoord concreet en gebruik gepaste vis-termen



Noem 1 misleidend aspect in deze vis.

👎 Er wordt 3D gebruikt.

👍 De 3D lijngrafiek vervormt het perspectief. Daardoor lijkt het laatste datapunt in 2018 een record, terwijl de waarde in 2013 hoger was.

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Feedback op het vis-gedeelte

Vul Caracal in!

Kom even babbelen (bv. Teams of BBG 4.21)

Hoe behulpzaam waren de slides en oefeningen?
Welke onderwerpen waren wel/niet interessant?
Waarom waren de hoorcolleges wel/niet nuttig?
Waarom waren de werkcolleges wel/niet nuttig?


The End
NOW I'M SAD

Hoorcollege 4

Visualisaties in rapporten

Interactieve visualisaties

Informatie-uitwisseling: informatievisualisatie

Jeroen Ooge

Universiteit Utrecht