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Data-Driven Storytelling with Data Comics

Benjamin Bach,
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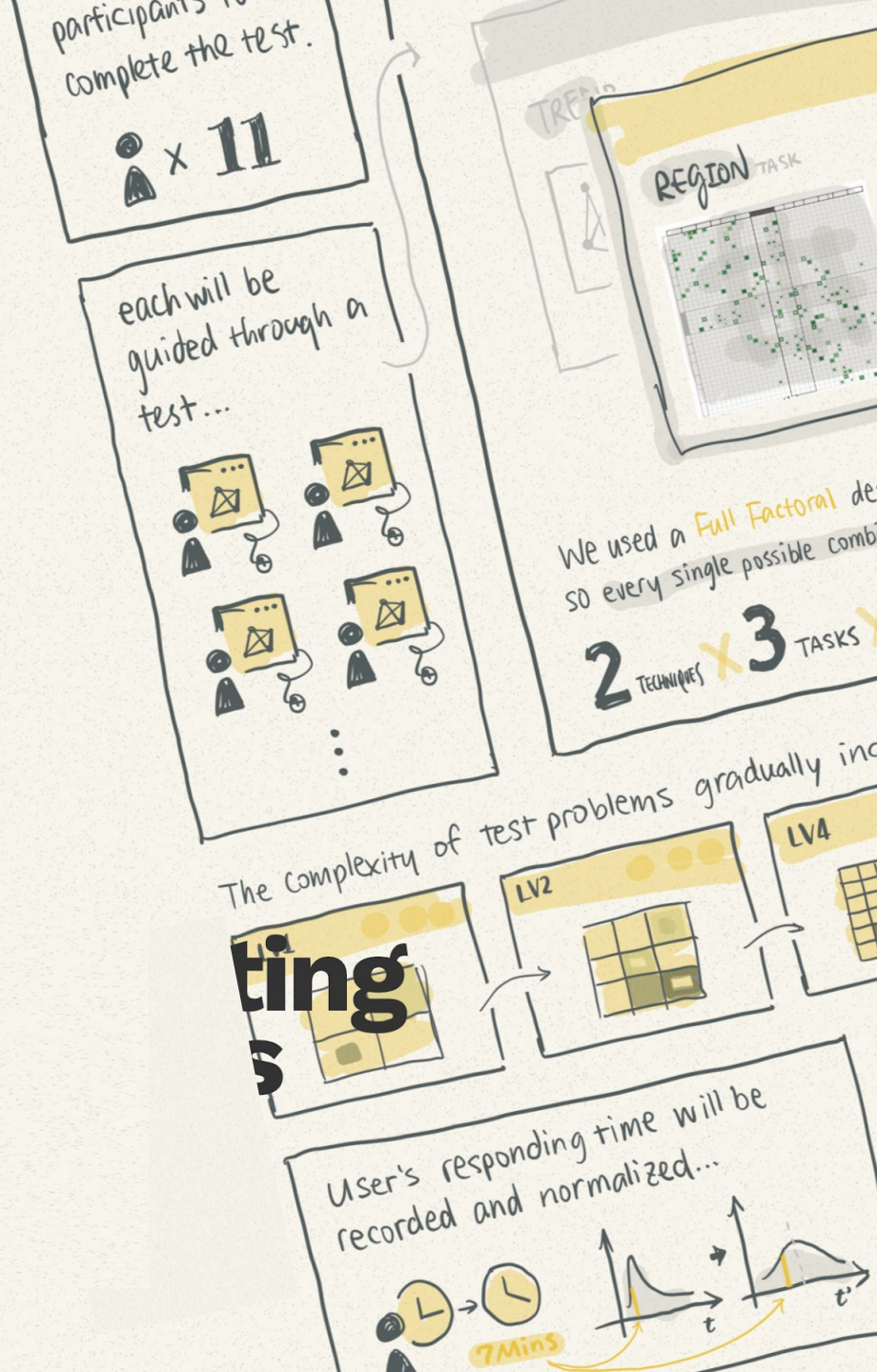

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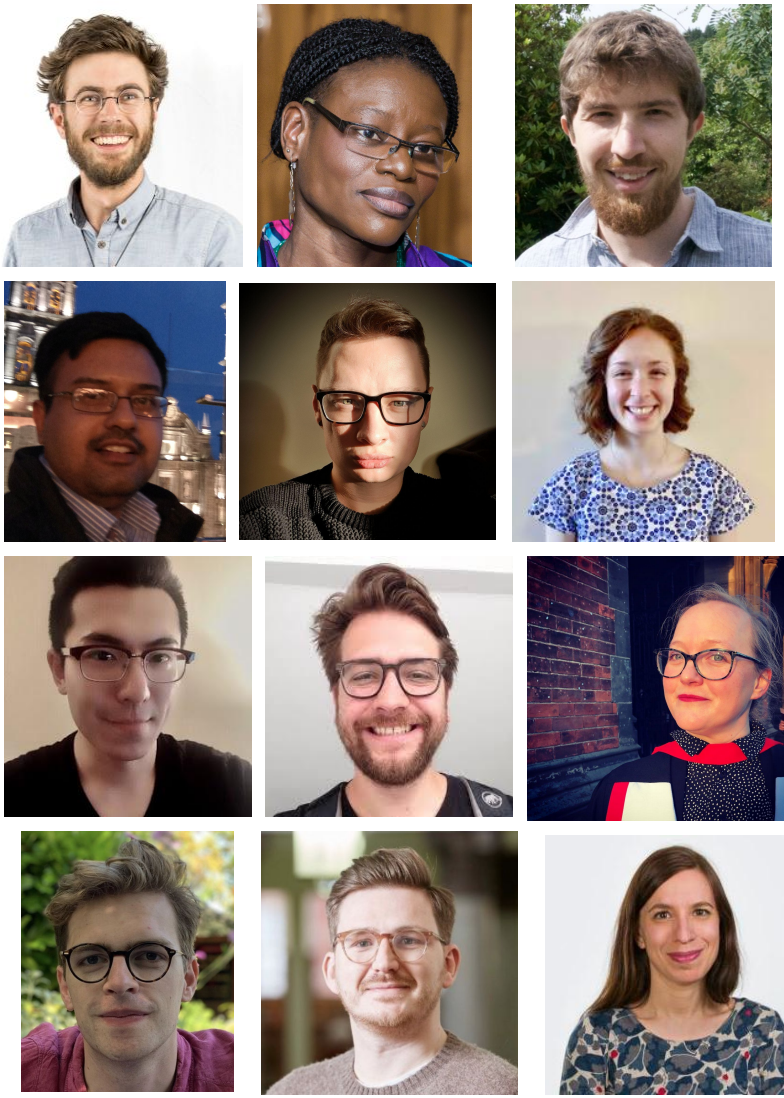

https://datacomics.github.io/designpatterns.html

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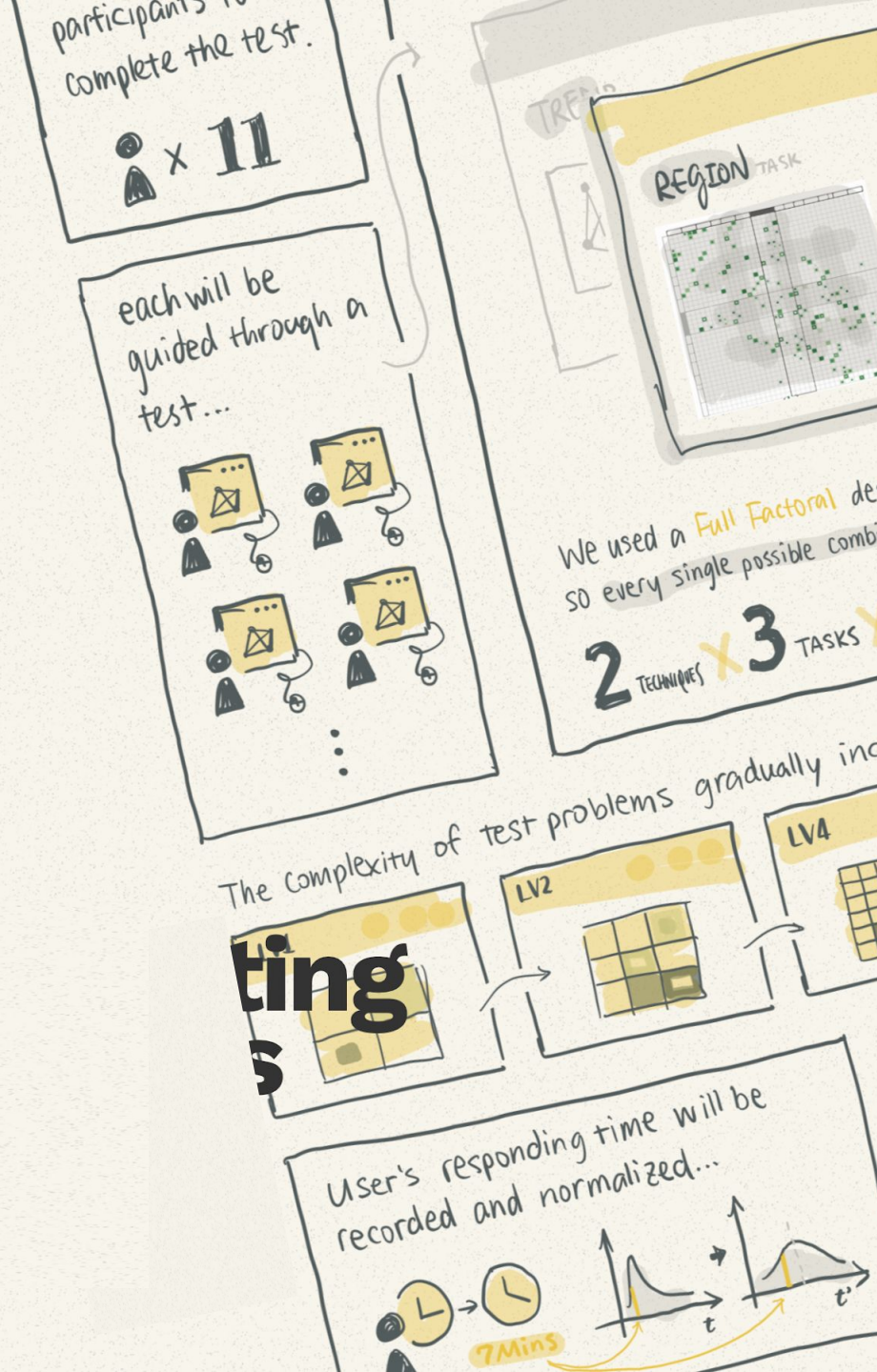


in space. We expect *TabletAR* to perform slower and potentially less precisely than *ImmersiveAR* due to the missing stereoscopic perception required for proper eye-hand coordination.

- $H_{training}$: *We expect participants to become both faster and more precise with increased familiarity over several days in the ImmersiveAR environment.* We assume that participants are well trained on the *Desktop* and that participants will get used to the *TabletAR* environment relatively quickly compared to *ImmersiveAR*.

4.5 Participants

We recruited 15 participants from the University's mailing list. 7 participants were undergraduates enrolled in an architecture program or related and were well trained in the usage of 3D CAD software on a traditional desktop. Four students were enrolled in a computer science program and well trained with mouse and keyboard interactions. Eight participants were male, seven were female. Two participants had previous experience with immersive VR technology and another two had previously used the HoloLens for a short time. Because the device is relatively new, our participants were novices with the HoloLens while all of them were well versed using the desktop. We do believe this reflects a typical scenario until wearable AR devices become truly ubiquitous. Yet, we were particularly interested in participants used to 3D visualization as immersive environments would be of special use to such users.

4.6 Procedure

We followed a full-factorial within-subject study design and blocked participants by environment. While environments were balanced using a Latin square (3 groups), task order was fixed to *distance*, *cluster*, *selection*, and *cuttingplane*. We decided on this order to increase perception and interaction complexity with each task. We report performance measures for each task individually.

Each condition (environment × task) started with 3 non-timed training trials followed by 6 timed study trials. Participants were told to be *as fast as possible*. Tasks were explained by the instructor using text instructions and examples printed on paper. During training, the instructor made sure participants correctly understood the task and could perform the required interactions to solve and finish the task. For each environment (*Desktop*, *TabletAR*, *ImmersiveAR*), the instructor explained the technology and helped participants with setting up.

During each of the 9 trials (including training) we measured task-accuracy and task-completion time from the start of the trial until the trigger event. We tracked positions of the visualization and the camera as well as the relative rotation between them. When participants clicked the trigger button to end a trial, an answering menu was brought up. In *Desktop* and *TabletAR*, the answer menu was shown in the center of the screen. In *ImmersiveAR*, the menu was shown always on the same wall in the study room for all participants, tasks, and trials. Participants were told to first issue the trigger—and hence stop the timer—and then turn to the menu to specify their answer.

Participants could take breaks between trials whenever the timer was not running. In *ImmersiveAR*, the instructor reminded participants to take breaks. Breaks could be taken as long as necessary in all conditions. The study was conducted in a quiet and well illuminated room with enough space for participants to freely walk around the hologram if desired. After the study, we asked each participant to fill out a questionnaire, indicating for each environment the participant's comfort and fatigue, the interaction's ease-of-use, as well as how each of the display conditions supported or hindered the tasks.

4.7 Long-term Training Condition

A random subset of 6 (out of 15) of the study participants was invited for a special condition to study the effects of familiarity/training on *ImmersiveAR* performance. Participants came back to the lab for 5 consecutive days to only perform the *ImmersiveAR* condition. Tasks, task order, and task difficulty remained the same. However, we generated new data for each session and for each of the 9 trials using the methods described in Sect. 4.3. On average, participants spent 15-20 minutes on the *ImmersiveAR* condition each day. We report the results of this *long-term training* group separately in Sect. 5 and Sect. 6.

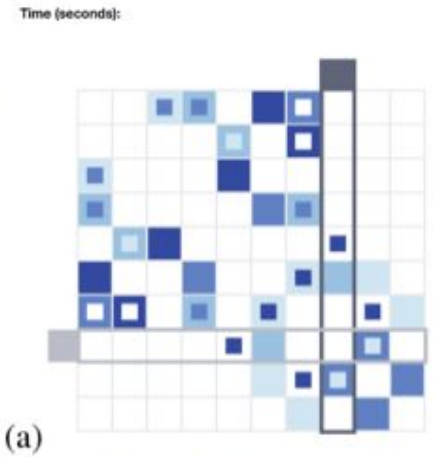


Fig. 7. Results for *time* (seconds), *error*, and subjective reported precision (5-point Likert scale) by task. Confidence intervals indicate 95% confidence for mean values. Dashed lines indicate significances for $p < .05$. Highlighted bars indicate significant best results.

5 Results

We now report on the results of our user study with respect to time, accuracy, user strategies, and subjective user feedback.

5.1 Task Completion Time and Accuracy

On average, it took each participant 1.5 hours to complete the study on all three environments. For each of the 4 tasks, we obtained 270 recorded trials (15 participants × 6 trials × 3 environments), excluding the 3 training trials per condition. We found time and error to not be normally distributed and we were not able to correct to normal distribution through logarithmic or any other transformation. To find outliers, we hence visualized the individual distributions of values for both *time* and *error* for all tasks and environments. Some of these outliers were quite extreme and we decided on above 60 seconds and below 1 second to be good thresholds for removing outliers. In total, we found 19 outlier trials across all tasks. Trials taking longer than 60 seconds may have resulted from technical problems, such as clicker malfunction; trials below 1 second were attributed to accidental clicks ending the trial early. The distribution of outliers per technique was as follows: *Desktop*=2, *TabletAR*=6, *ImmersiveAR*=11. By removing outlier trials, we obtained an unequal number of trials and used the non-parametric Friedman-Chi-Square test for null-hypothesis testing, as well as Mann-Whitney-U test for pairwise significance testing.

Significance values are reported for $p < .05$ (∗), $p < .01$ (∗∗), and $p < .001$ (∗∗∗), respectively, abbreviated by the number of stars in parenthesis. Numbers in parentheses indicate mean values in seconds (time) and mean-errors in the specific unit for each task. Results for time and error are shown in Fig. 7. Confidence intervals indicate 95% confidence. We report time and error measures for each task separately.

Distance: We found significant (∗∗∗) differences for *time*. *Desktop* (7.8s, SD=4s) was found to be faster (∗∗∗) than both *TabletAR* (12.9s, SD=9.1s) and *ImmersiveAR* (12.9s, SD=9.4s). For *error*, Friedman-Chi-Square test did not find significant differences. However, the pairwise comparison with Mann-Whitney-U test revealed *Desktop* (.09, SD=.3s) to be more precise (∗) than *TabletAR* (.18, SD=.4s). No significant difference was found between *ImmersiveAR* (.13, SD=.3s) and *TabletAR* (.18, SD=.4s), though *ImmersiveAR* was slightly faster than *TabletAR* on average. We thus can fully accept $H_{distance-time}$ but have to reject $H_{distance-error}$ due to the lack of significance. We conclude that users were faster *and* more accurate with *Desktop*, confirming earlier findings [60].

Clusters: We found significant differences (∗∗∗) for *time*, with *Desktop* (9.2s, SD=5s) being the fastest (∗∗∗) (*ImmersiveAR*=17.2s, SD=11s, *TabletAR*=16.2s, SD=9s). We can thus fully accept $H_{cluster}$. The time difference is likely due to the time required to physically move one's head or the marker. For *error*, Friedman-Chi-Square test found a significant effect of the task (∗∗). Pair-wise comparison with Mann-Whitney-U test found *Desktop* (.16, SD=.4) and *ImmersiveAR* (.16, SD=.4) to be more precise (∗∗) than *TabletAR* (.33, SD=.5). This result came as a surprise. Since *TabletAR* featured components of the two other environments (monoscopic display and marker interaction) we attribute the increase in precision to the ease and precision in rotation in *Desktop* and stereoscopic vision coupled with head-movement in *ImmersiveAR*.

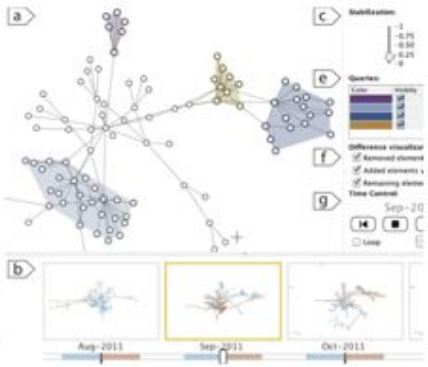
Selection: We found highly significant differences (∗∗∗) between all environments for *time*. *ImmersiveAR* (19.7s, SD=9s) was slowest (∗∗∗) while *Desktop* (6.7s, SD=3s) was fastest and significantly (∗∗) faster than *TabletAR* (8.6s, SD=4.7s). We thus have to reject $H_{selection}$. We attribute the lack of speed of *ImmersiveAR* to the time required to move one's head and body around the visualization. For *error*, we found *TabletAR* (2.7, SD=2.8s) to require more (∗∗∗) clicks (touches) than the other two conditions (*ImmersiveAR*=1.3 (SD=1.7), *Desktop*=1.7 (SD=2)). We attribute this to the fat-finger problem as people can more accurately pinpoint smaller targets with the mouse. This was crucial in the *selection* task where some points were partly hidden and which required rotation of the model and hence added time in *TabletAR*. *ImmersiveAR* required fewer clicks than *Desktop*, indicating that in real 3D space participants could better judge when a marked cube was hit. While the precision of *ImmersiveAR* came at the price of speed, we observed that in *Desktop* participants sometimes interacted too fast and hence missed the respective targets.

Cuttingplane: We found significant differences (∗) for this task with respect to *time*. *ImmersiveAR* (18.6s, SD=11s) was faster (∗∗) than both *Desktop* (22.2s, SD=13.4s) and *TabletAR* (27.7s, SD=17s). For *error*, we found a trend towards significance ($p = .056$) for *Desktop* (22.7, SD=14.2) being less precise than *ImmersiveAR* (21.9, SD=13.8). We can thus accept $H_{cuttingplane}$, but state that generally high precision is possible in all three environments.

5.2 Interaction and Task Strategies

We were interested in participants' exploration of different strategies and affordances of the visualization environments, especially for *ImmersiveAR*. We did not force participants into a single strategy, e.g., to remain seated and rotate the marker. For *ImmersiveAR*, only 2/15 (13.3%) remained seated during all tasks, while the rest (86.6%) stood up after the first training trial and locked holograms in free space (air-lock in Fig. 1(a,c-d)). More than half of the participants (8/13) placed the visualization at the height of their head and eyes, while the others (5/13) placed the visualization hologram at the height of their chest, i.e., lower than head height. For *cluster*, participants reported on the convenience of moving themselves or their head around the air-locked hologram to observe it from all three orthogonal directions. One participant explicitly reported that she placed the visualization so that she faced all orthogonal directions to an equal extent, effectively reducing her time to move around it.

During *TabletAR*, only 2/15 (13.3%) participants stood up and moved the tablet around the visualization or the marker, while the rest remained seated and instead moved the marker. One observed problem during the *TabletAR* condition was that the distance between the marker and the screen had to be large, making viewing the tablet screen for some participants hard. The prevalent strategies for *Desktop* were fast rotation of the visualization (71%), while 35% of the participants also or exclusively rotated slowly.



we found was for *TabletAR* in the *selection* task; participants reported high precision but in fact produced many clicks that did not target the marked points in the visualization. For the same task, however, *ImmersiveAR* was reported to be less precise than *Desktop*, though the recorded data indicated precision as high as for *Desktop*.

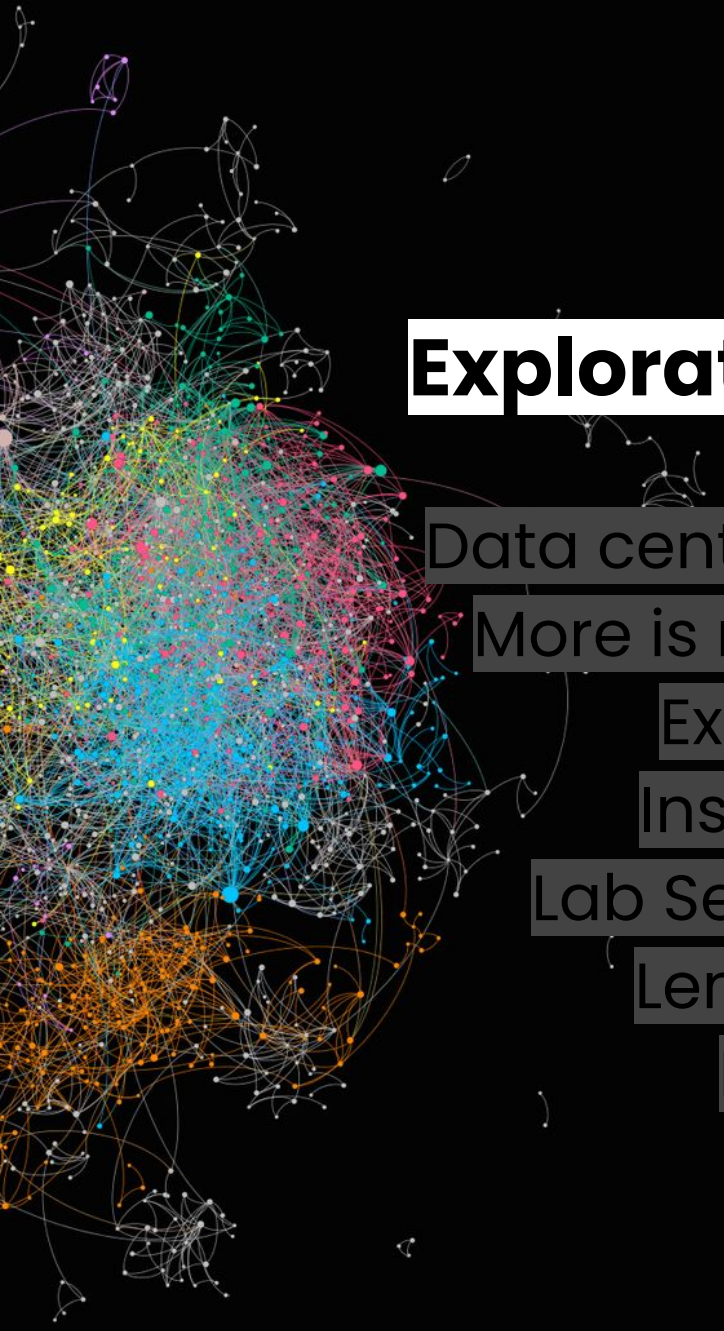
ImmersiveAR, understandably, was reported to be difficult to handle in the beginning but became more usable (*"I became accustomed to it in the end"*). The condition was also reported to be an attractive experience. Participants liked the spatial freedom and walking around (*"[I] loved the ability to walk around an object"*). They also positively reported on the stereovision (*"The hololens gives an instant understanding of depth [...]"*,*"ease with which I could judge distances/location"*, *"could see the space clearer"*), and spatial comprehension (*"comprehension was the highest with HoloLense* (SIC)*"*). However, interaction was more cumbersome (*"was very difficult to interact with."*, *"it's good as an experience but harder to for certain things beyond seeing, such as touching or slicing"*). One participant noted though she was prone to motion sickness, she did not feel any symptoms with the *ImmersiveAR*.

In *TabletAR* participants appreciated the easy and fast selection on the screen, but disliked the spatial mismatch between interaction and perception. One participant reported *"I felt constrained by the positioning of the camera in relation to the hologram markers. That could have been alleviated by moving the tablet just slightly but I didn't want to risk losing view of the marker"*. Others reported on the difficulty of manipulation *"holding tablet in hands contribute to imprecise manipulation."*, *"holding the tablet and markers involves a bit too much simultaneous manipulation to feel very precise."*. One participant suggested dragging objects on the screen, a setting common in other applications (e.g., [37]). In neither *TabletAR* nor *ImmersiveAR*, did the participants report complaints about the markers' patterns distracting them from the task or resulting in any visual interference with the visualization.

For *Desktop*, participants appreciated the ease and effectiveness of the environment (*"easier to complete [the tasks] on the flat screen"*, *"absence of Z parameter"*, *"the best interaction experience was with desctop* (SIC)*"*.) One participant summarized his/her experience as follows: *"To sum it up, Hololense* (SIC) *gives the best comprehension, Desctop* (SIC) *gives the best manipulation."*

5.4 Long-Term Training

To understand the effect of training for the *ImmersiveAR*, we analyzed the four additional sessions for the long-term training group (6 participants). Training was performed once a day, at the same time, for the four days following the participant's first session with the *ImmersiveAR*. We analyzed each task, data set, and participant individually as we believed there would be differences between participants. In particular,



Exploration	Explanation
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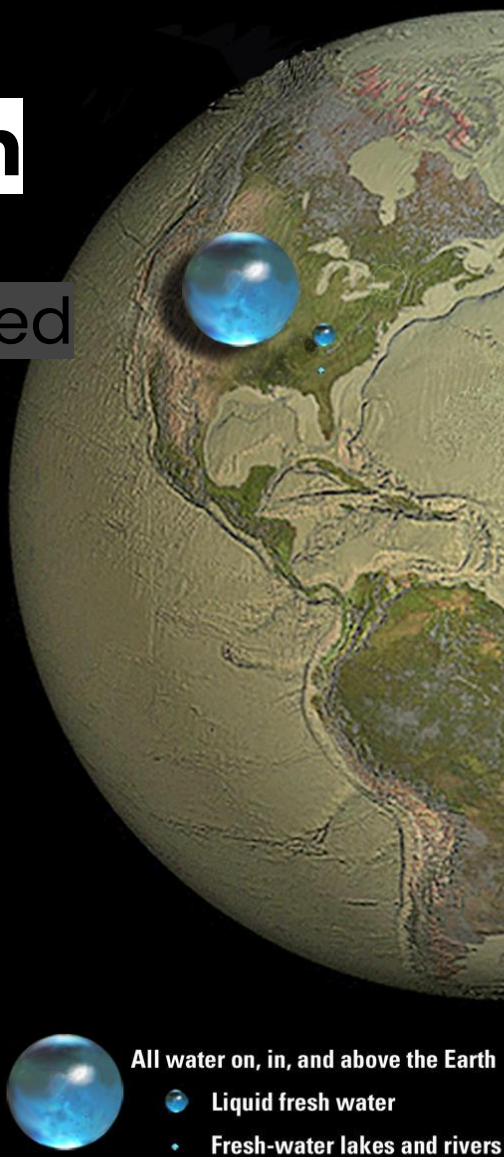
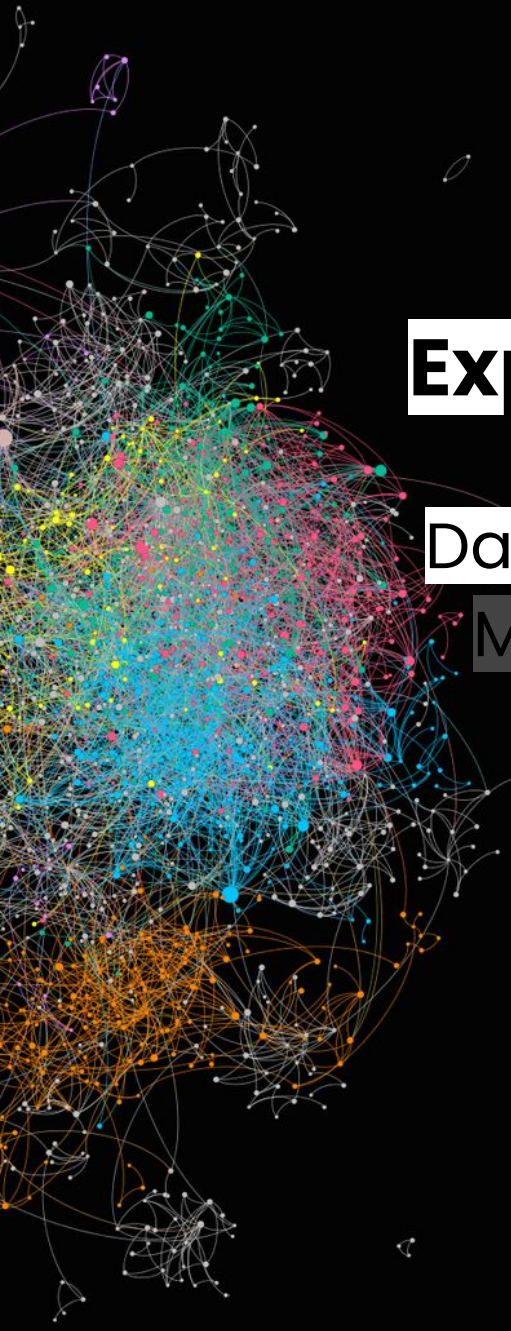
More is more	Less is more
Experts	Non-experts
Insights	Messages
Lab Setting	In-the-wild
Lengthy	To-the-point
Fuzzy	Precise





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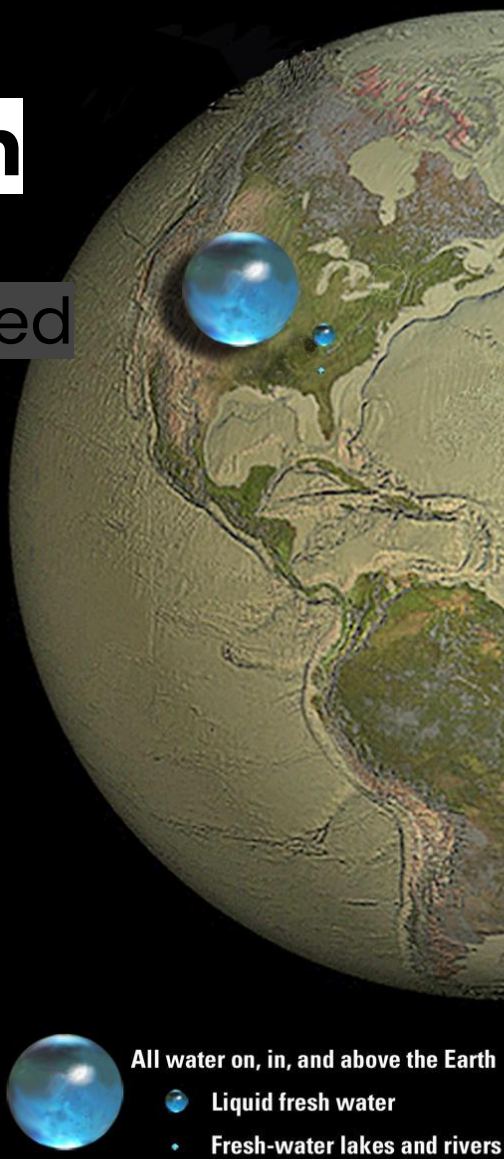

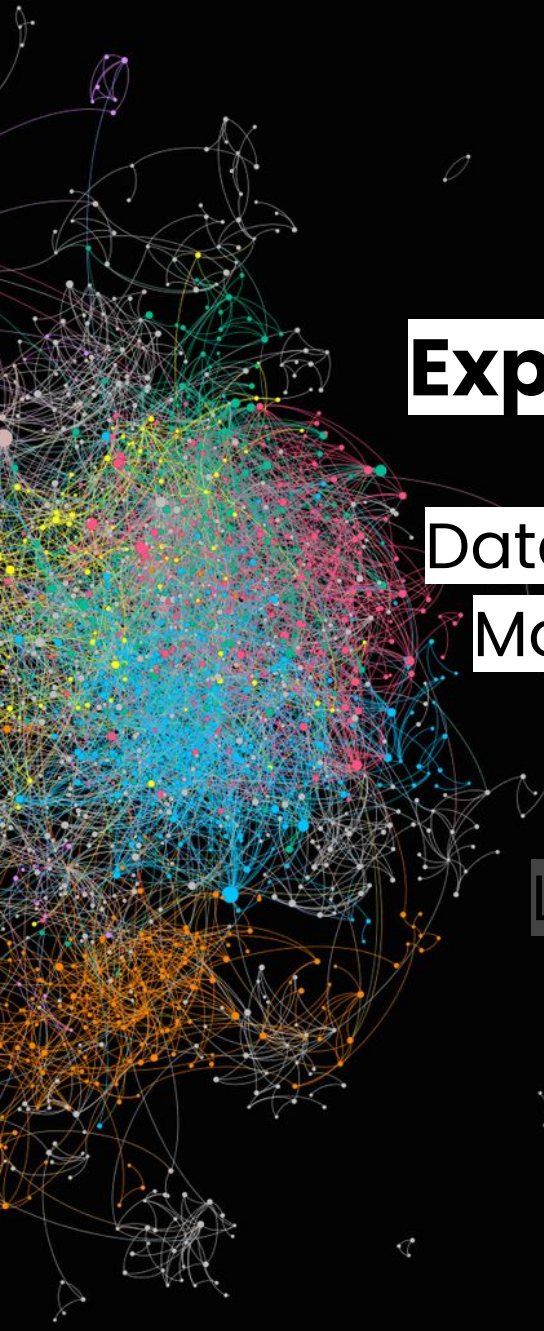

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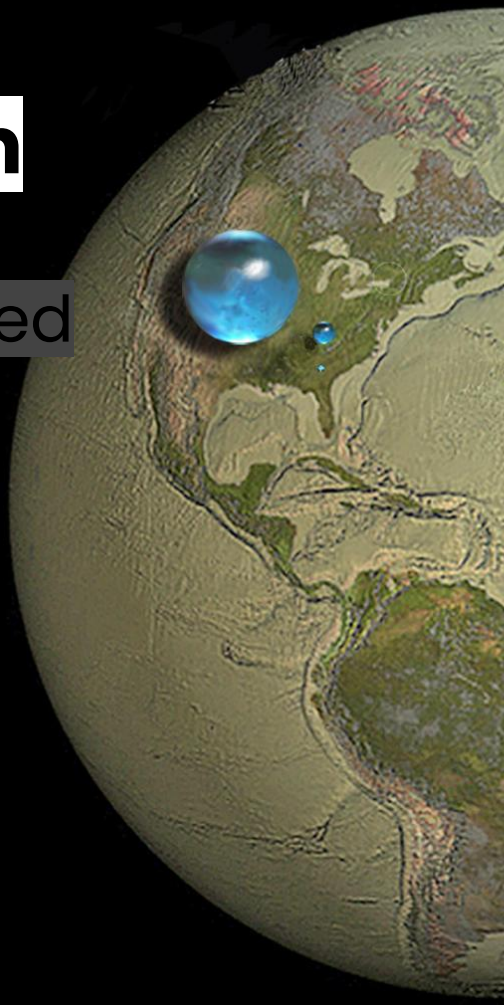

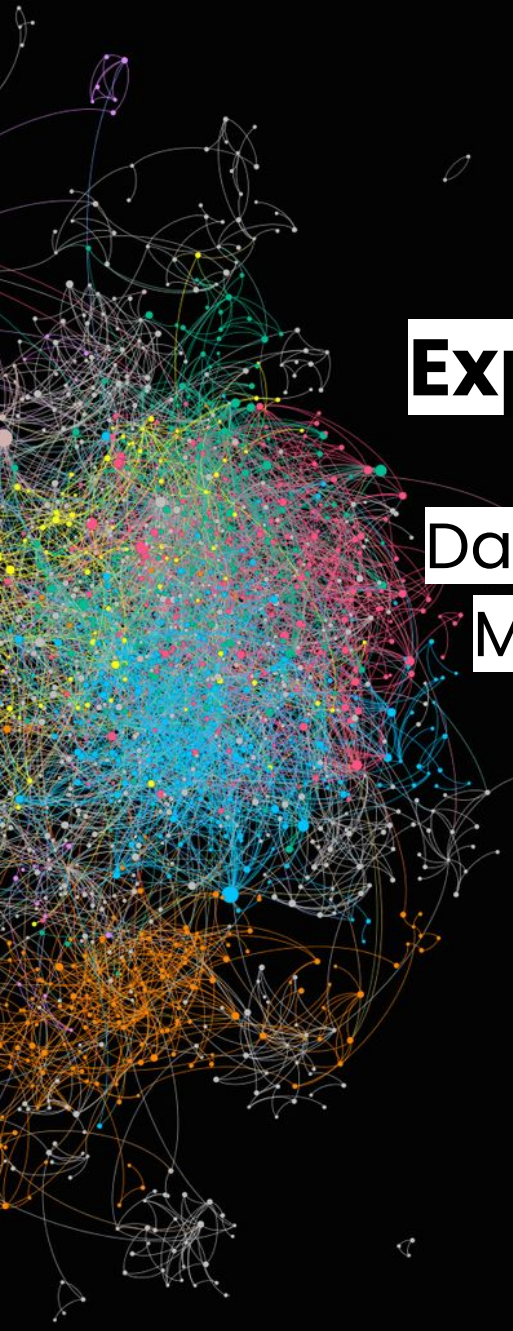

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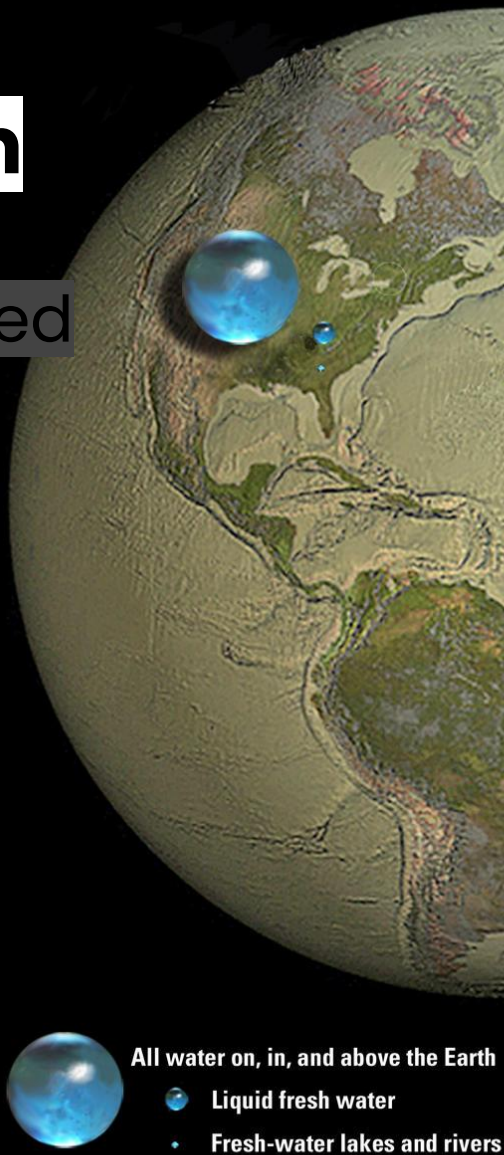

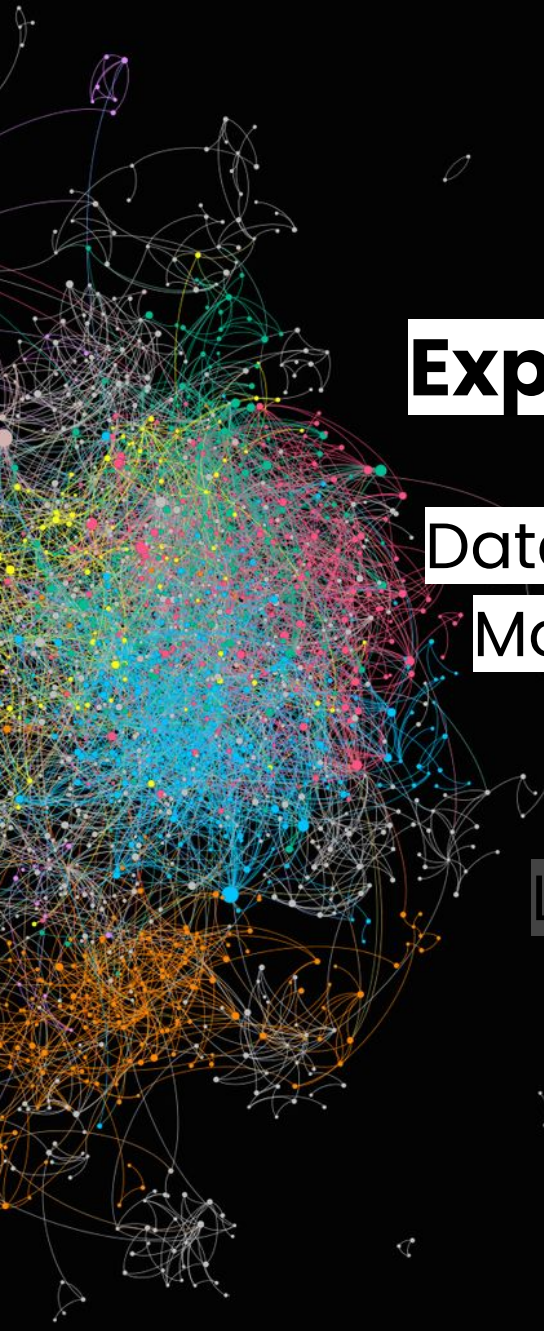

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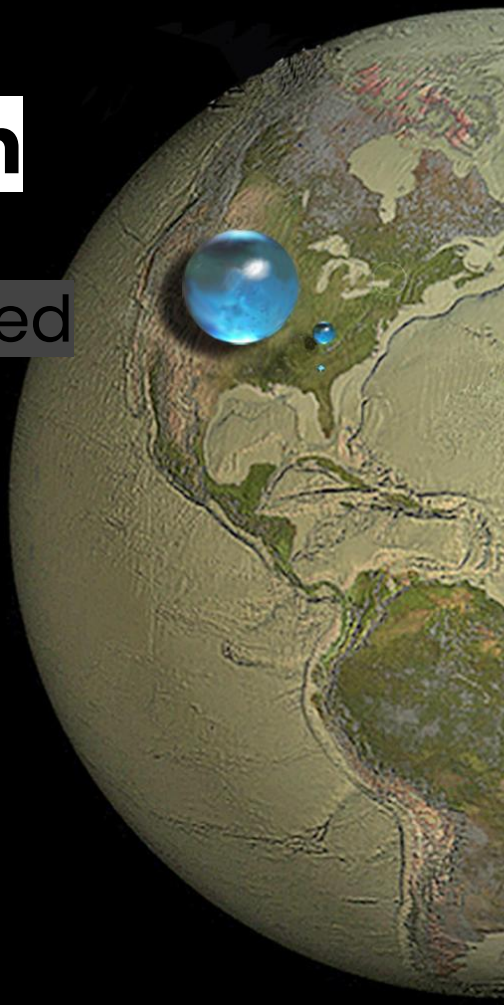

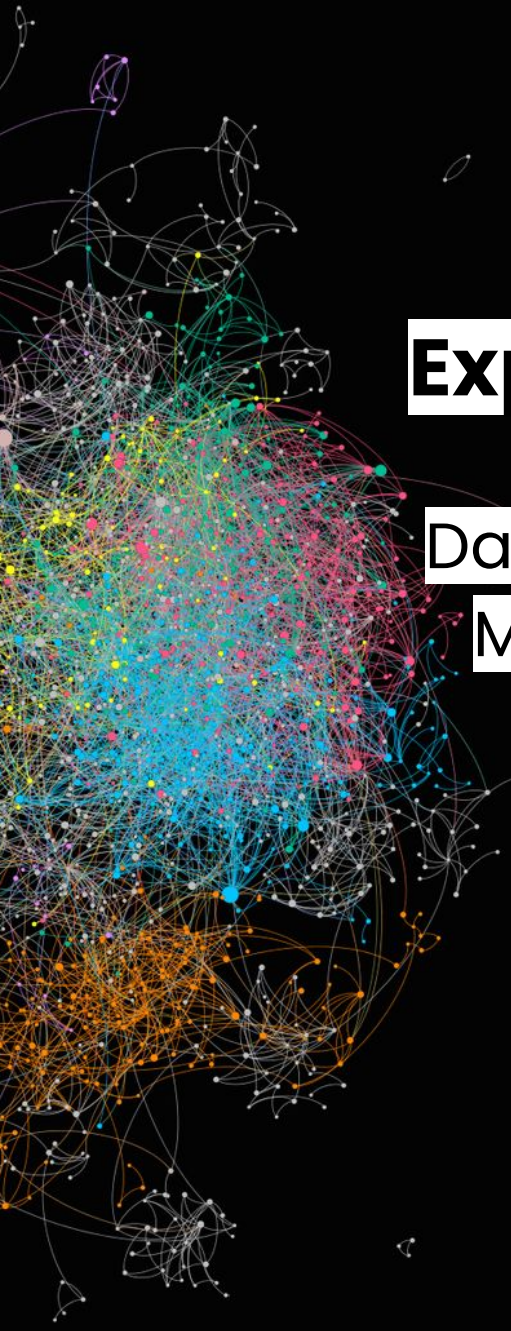

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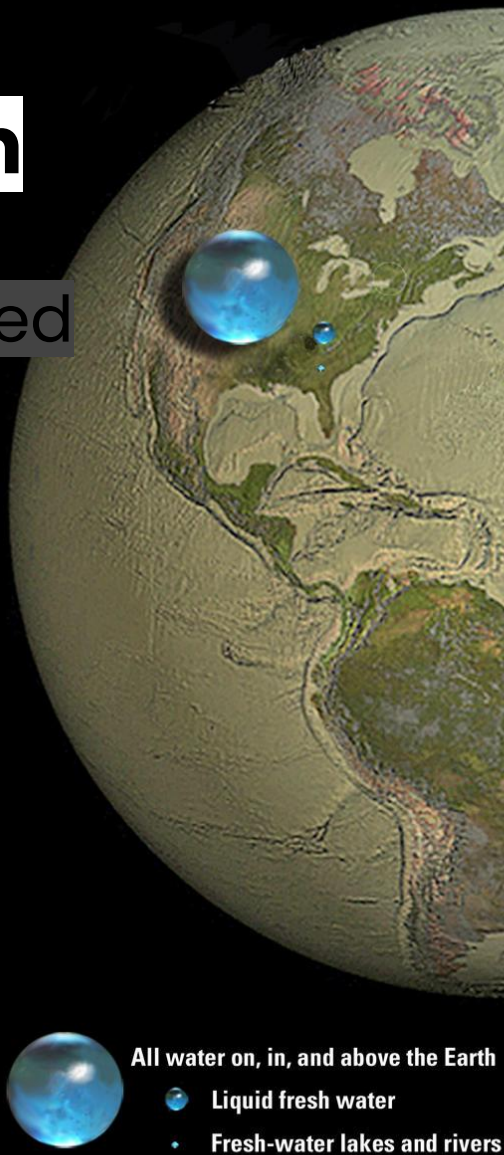

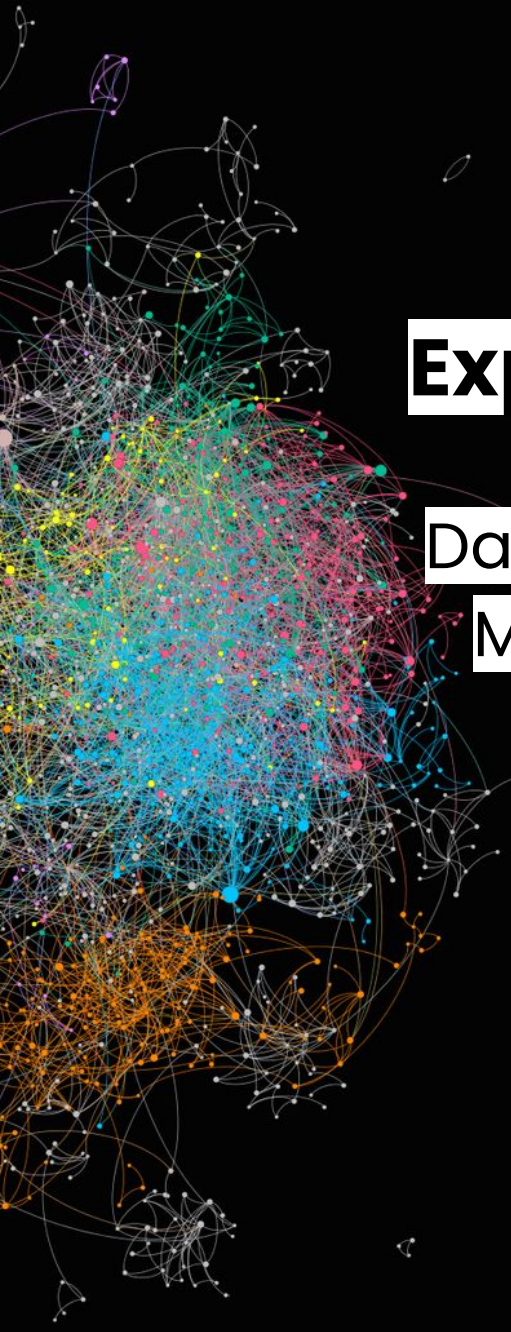

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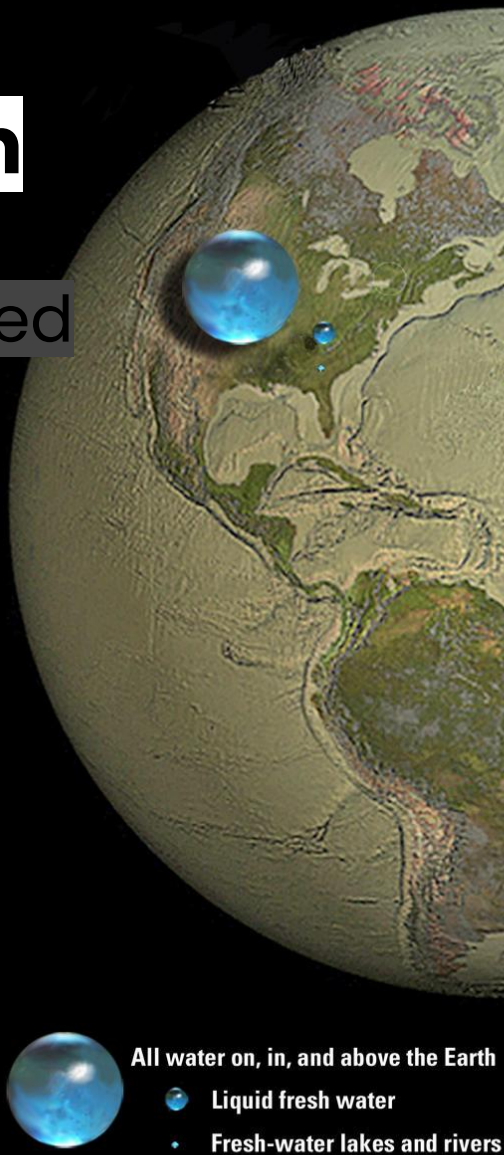

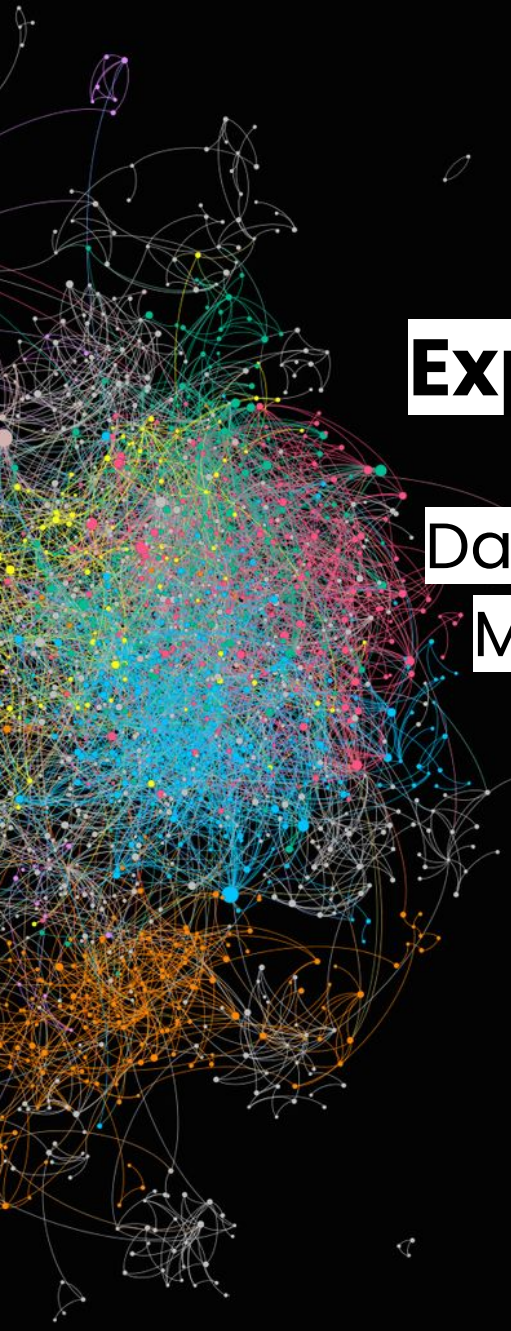

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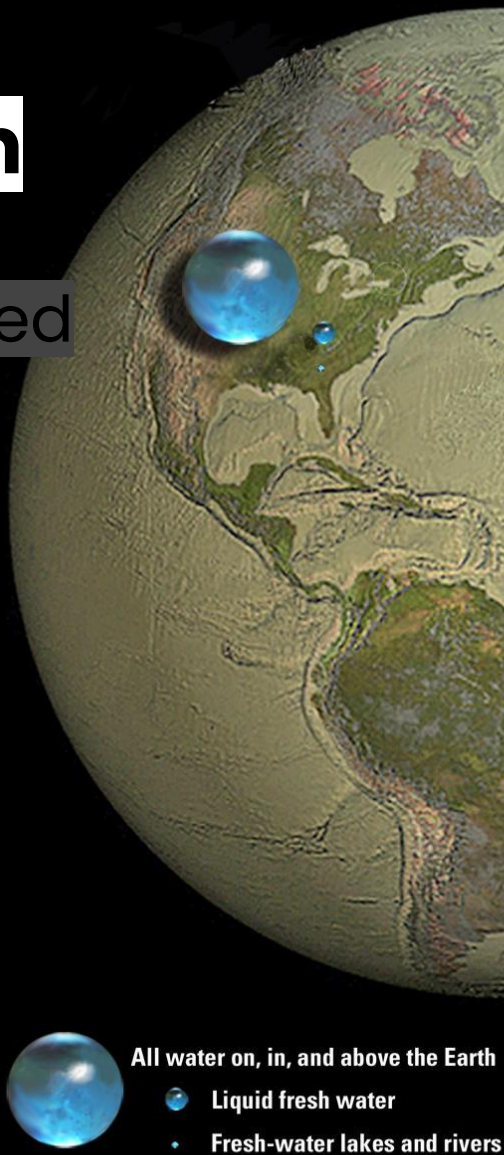

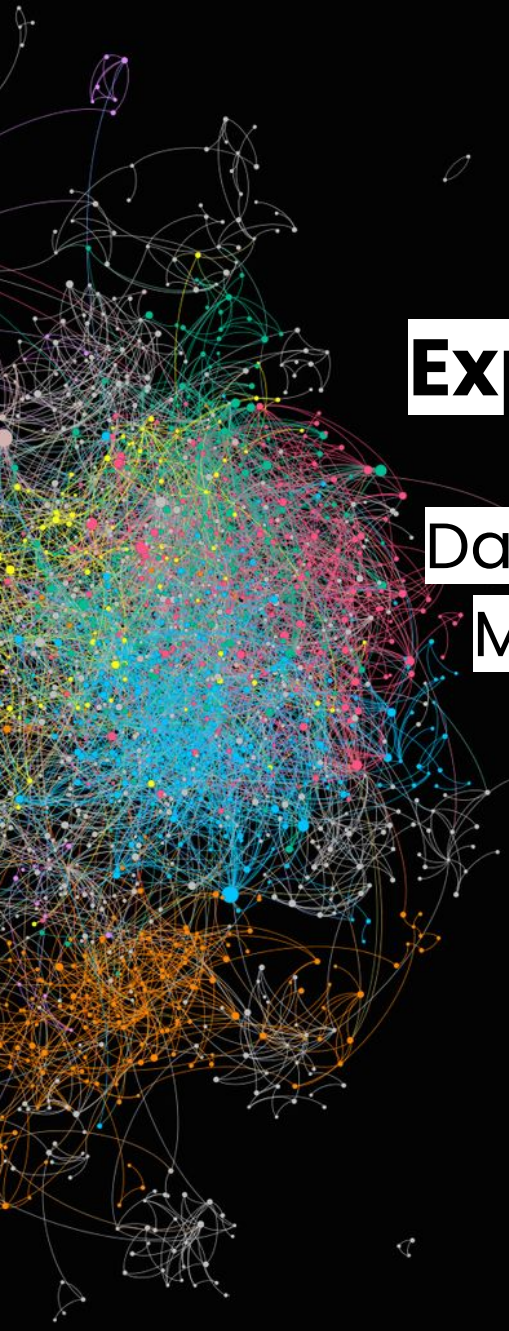

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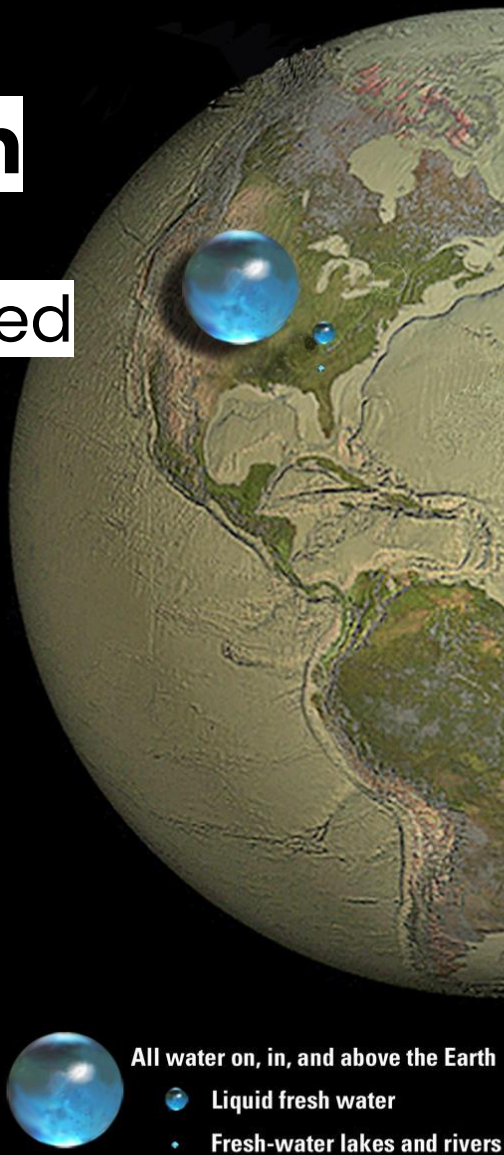

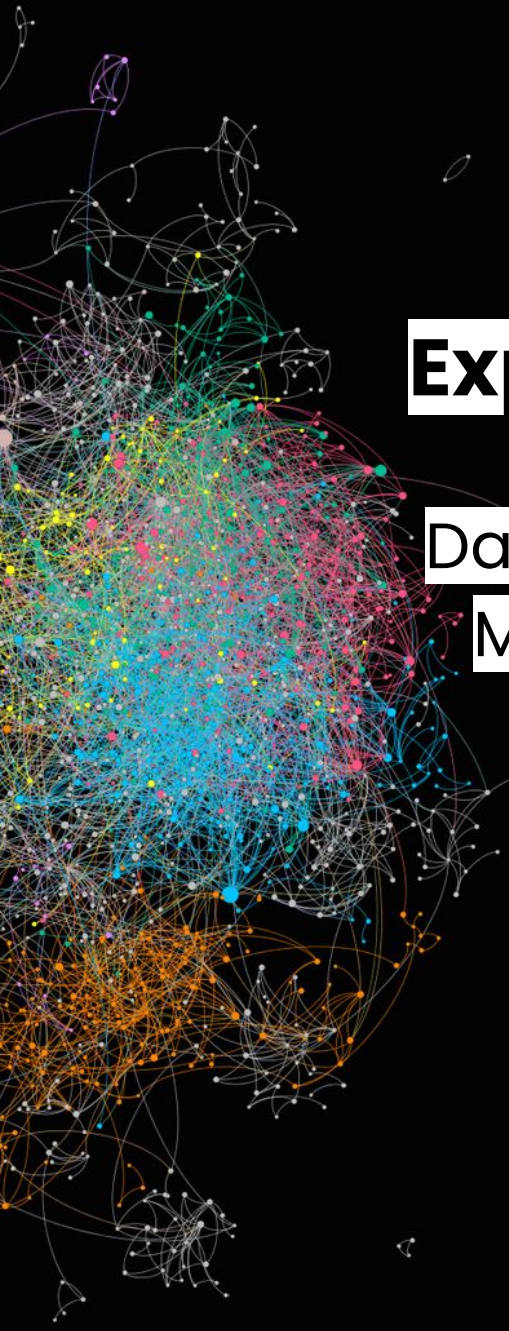

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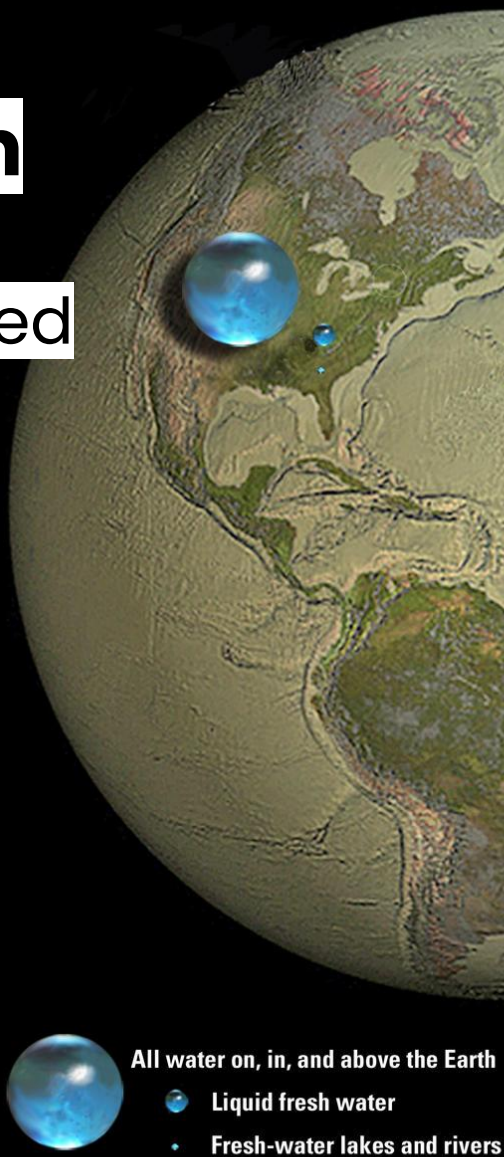

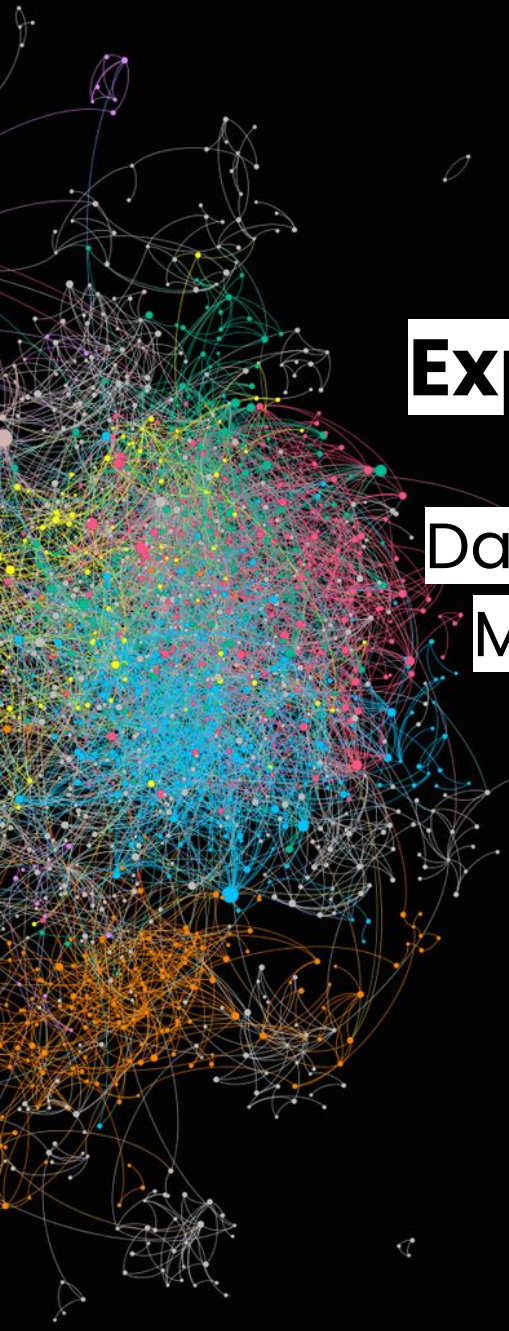

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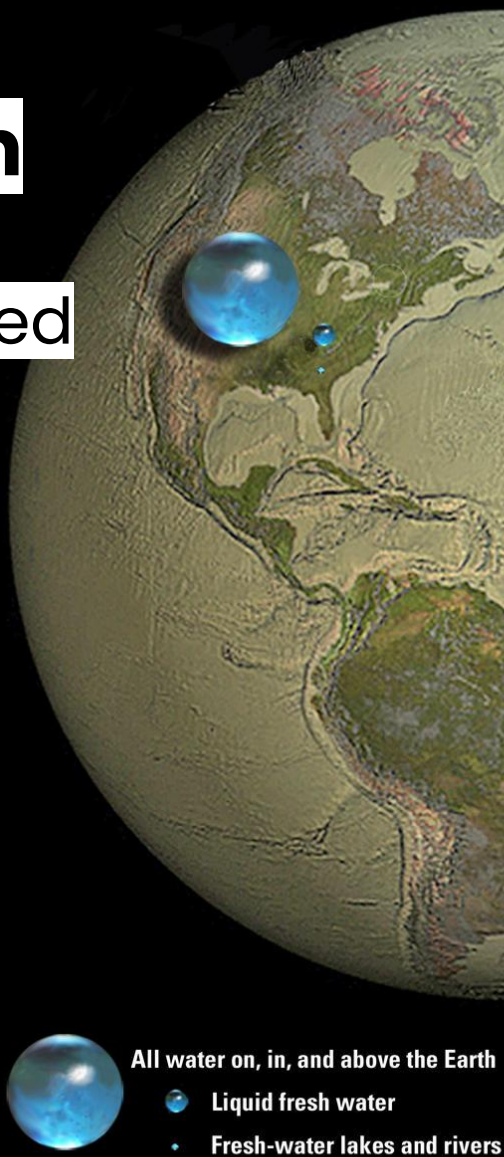

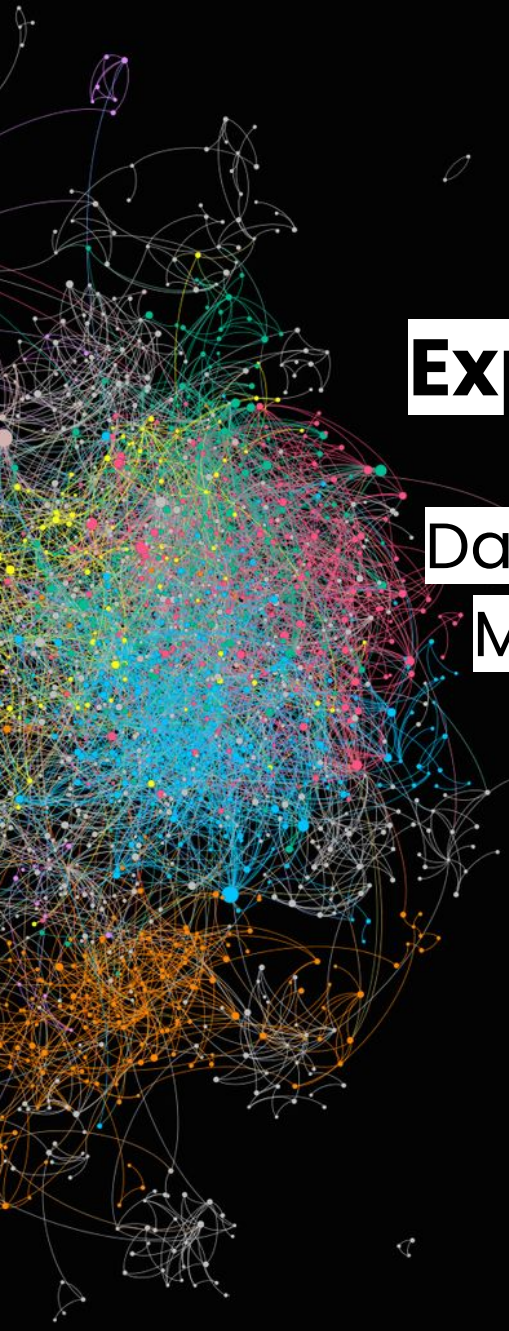

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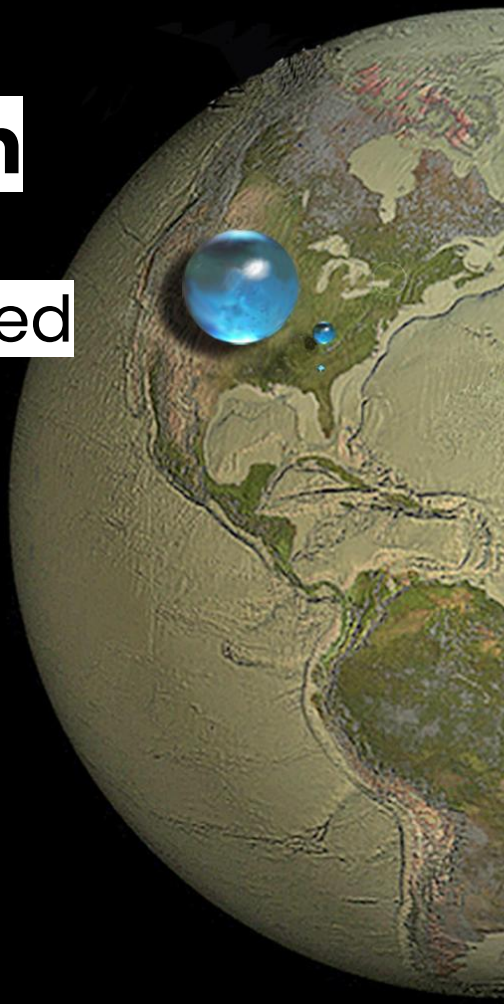

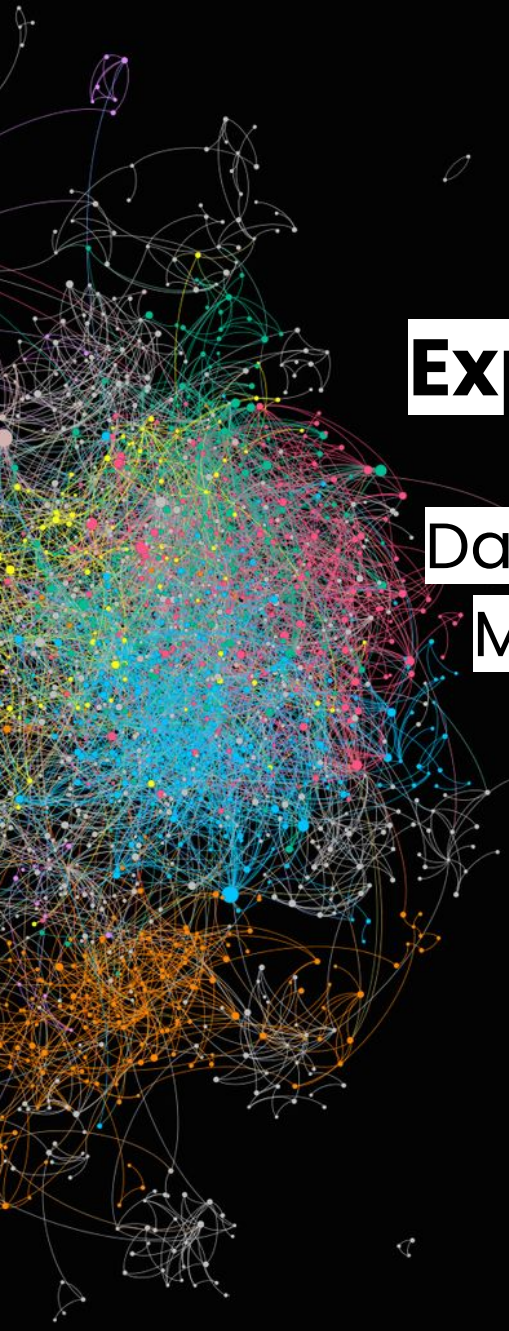

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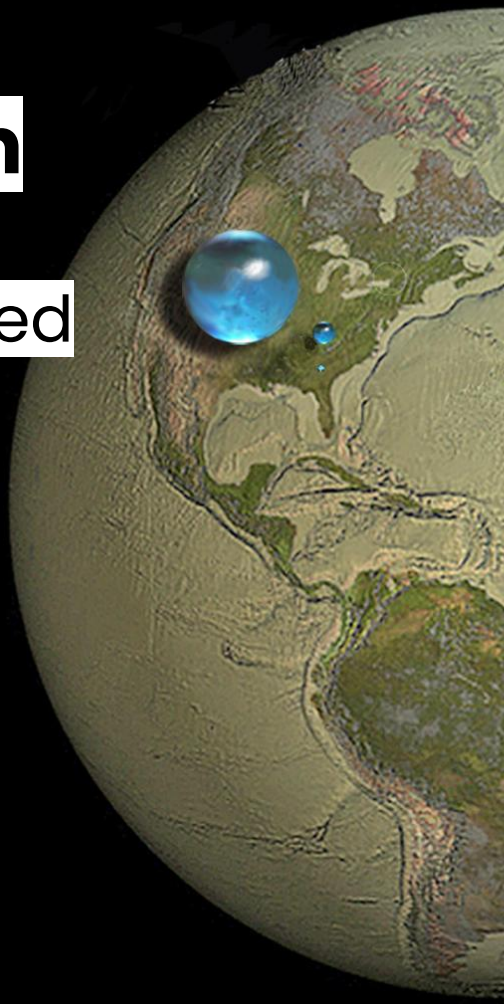
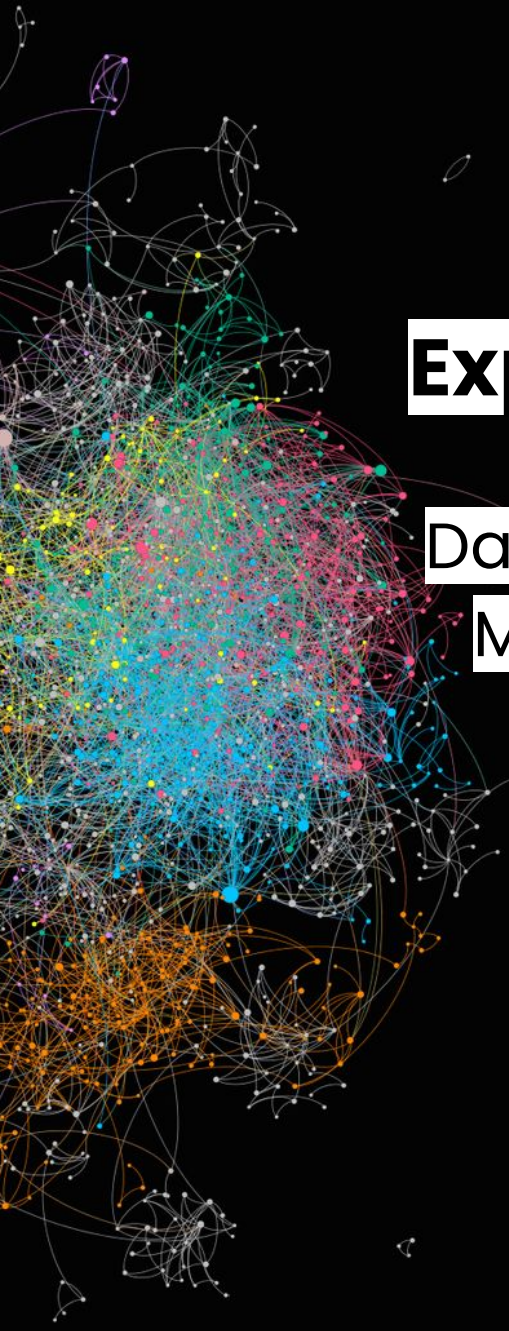
Data centered	Human centered
More is more	Less is more
Experts	Non-experts
Insights	Messages
Lab Setting	In-the-wild
Lengthy	To-the-point
Fuzzy	Precise





Exploration	Explanation
Data centered	Human centered
More is more	Less is more
Experts	Non-experts
Insights	Messages
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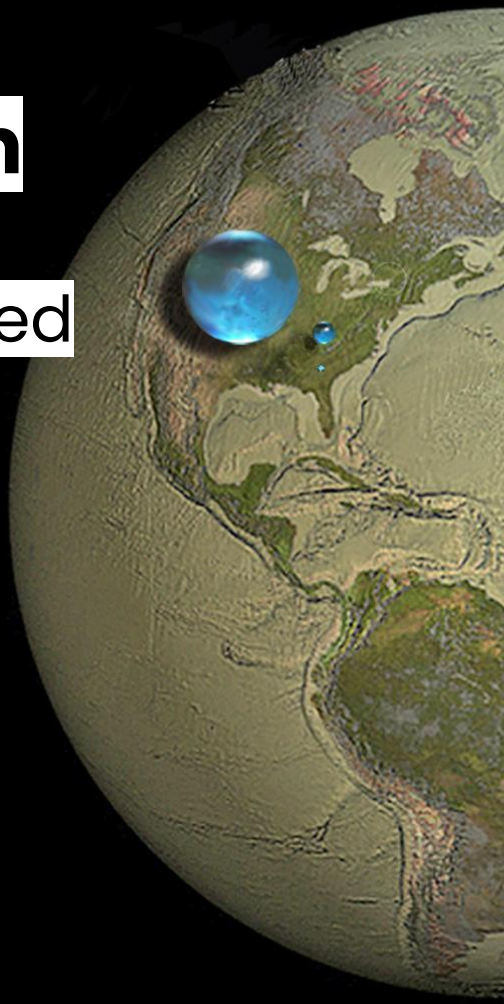

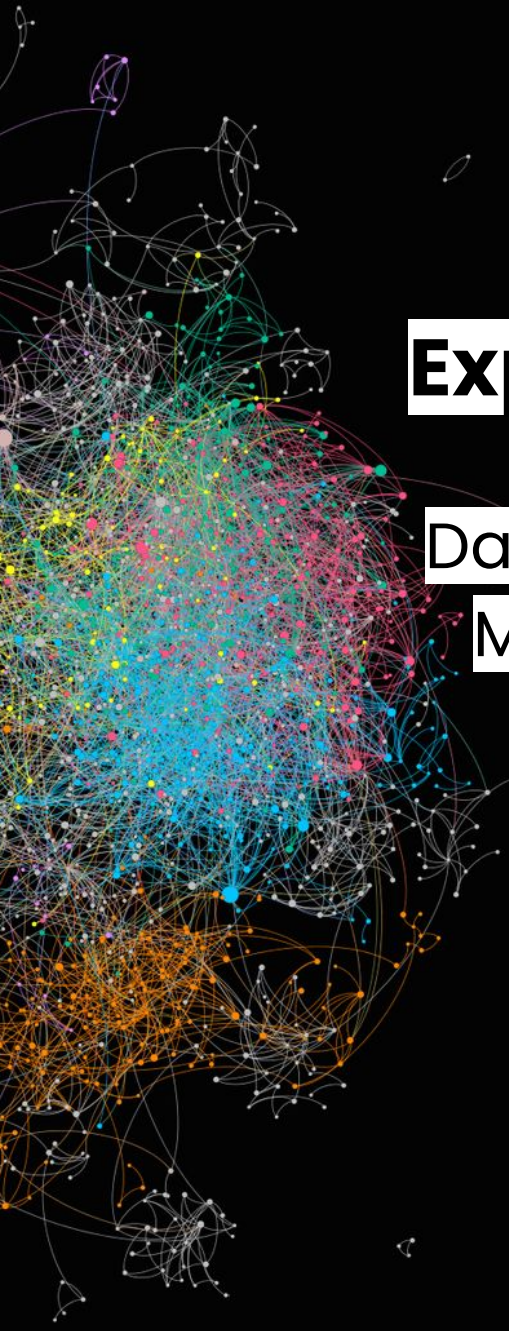

Exploration	Explanation
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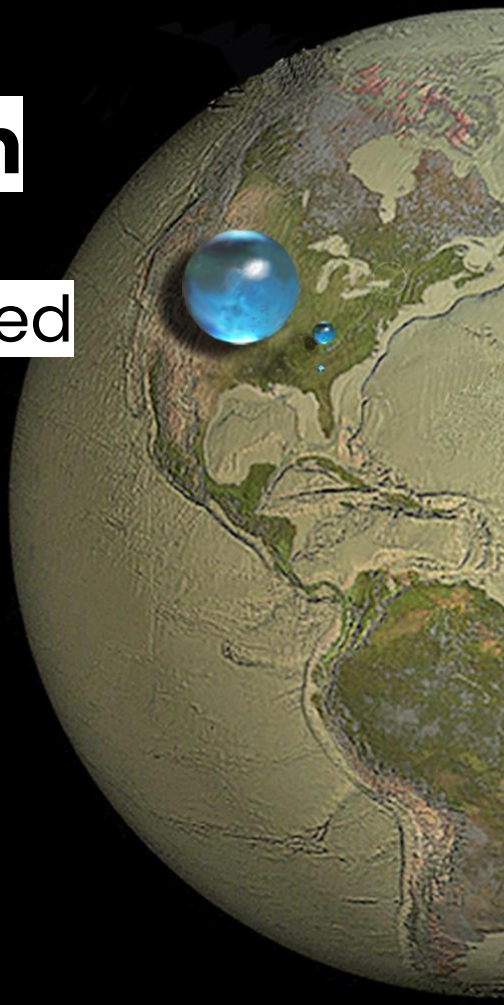


graphic design

Drawing & illustration

storytelling

Skills

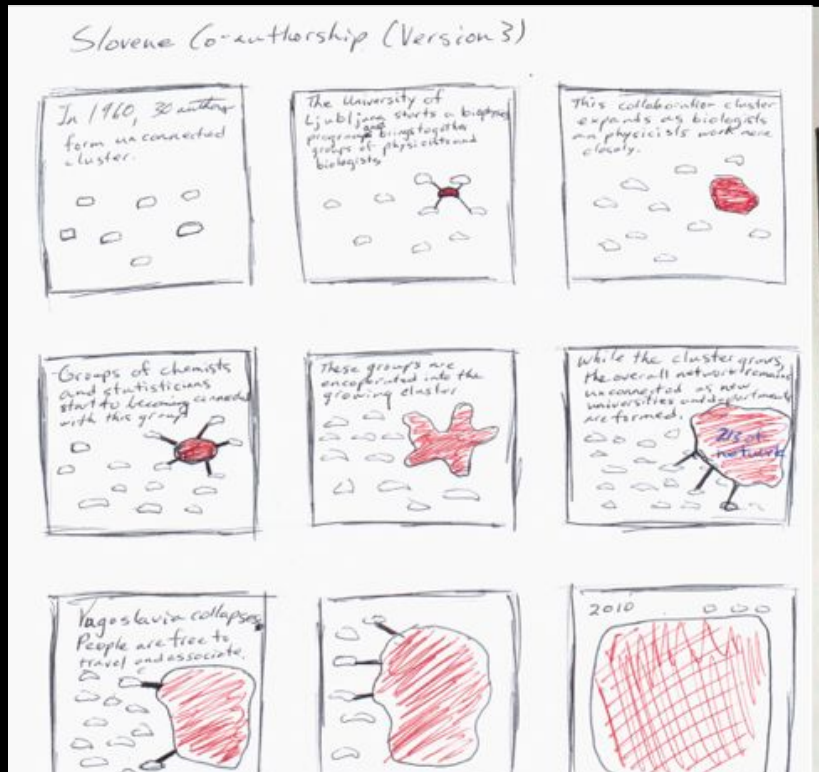
visualization
design

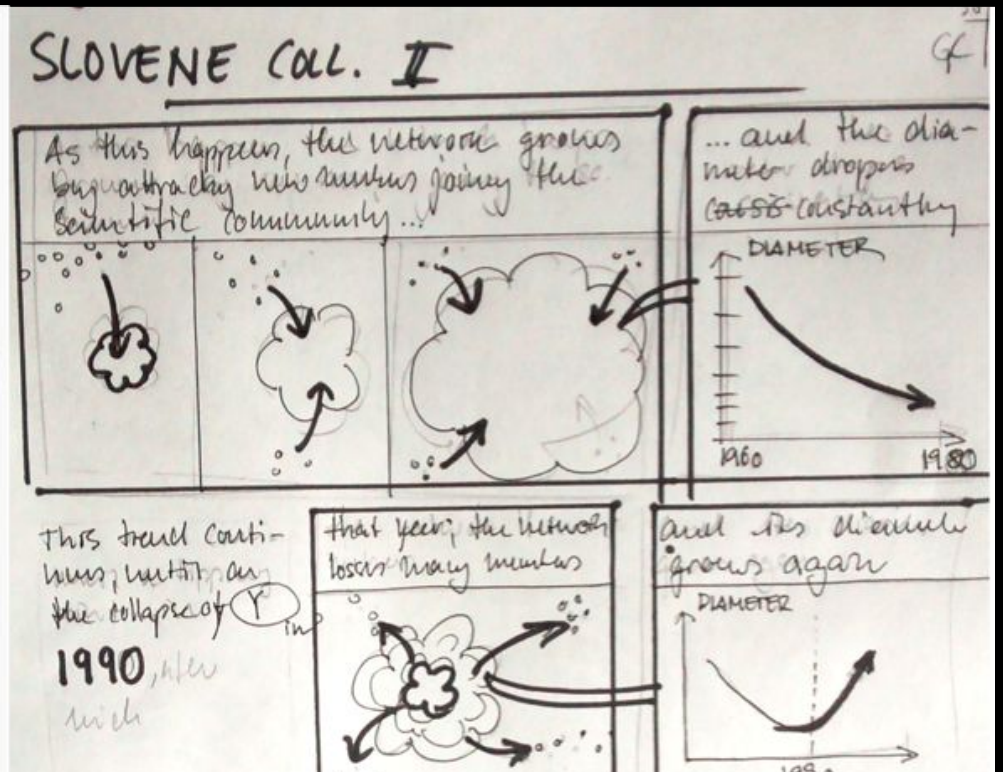
data analysis

creating
visualizations

Goals

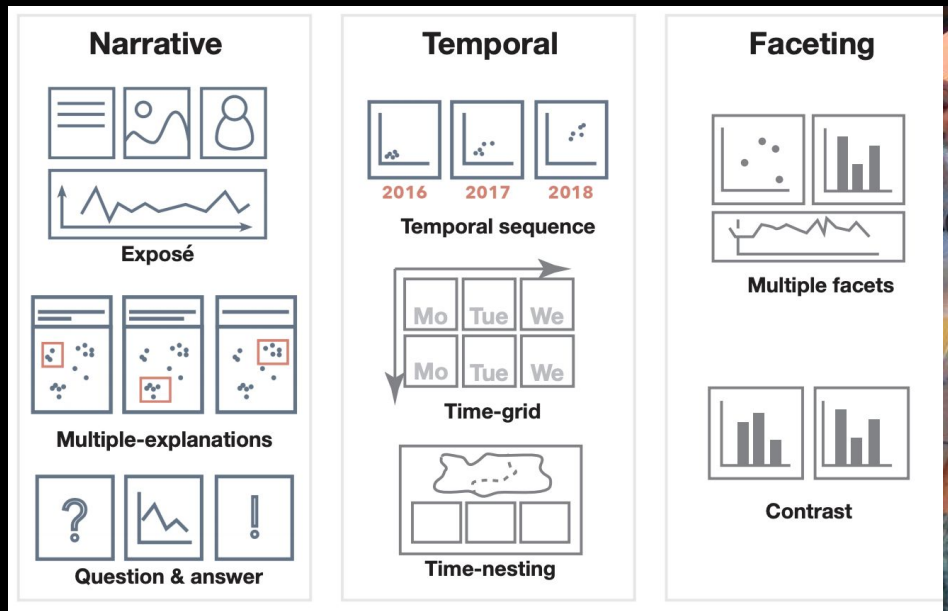
- Basics of storytelling
- Storytelling with visualization
- Know storytelling formats
- Create data comic storyboard

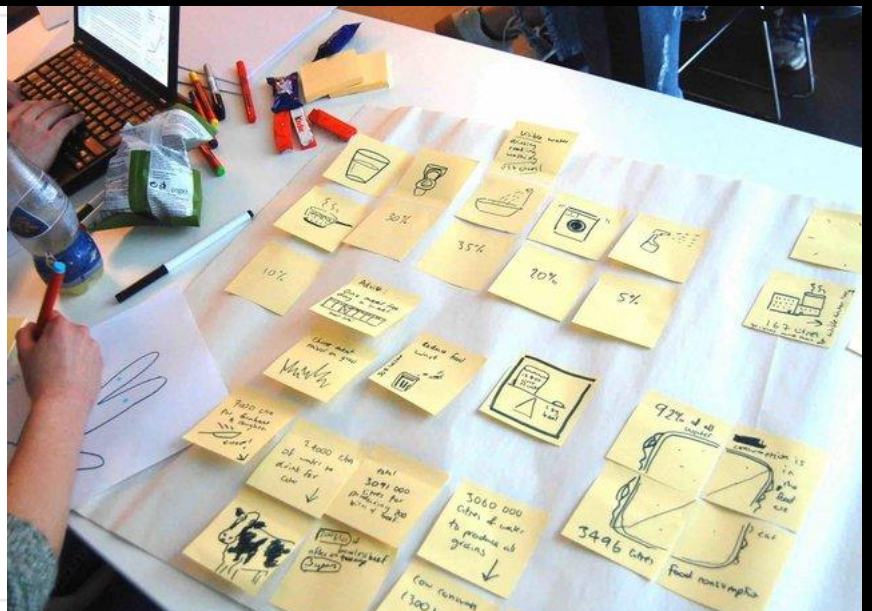




Outline

- Activity 1: Audience (10min)
- Activity 2: Messages (15min)
- *Activity 3 : Scripting (20min)*
- *Break (15min)*
- Activity 4: Visualizations (20min)
- Activity 5: Storyboarding (30min)





https://miro.com/app/board/o9J_l5lHst4=/

THE UNIVERSITY of EDINBURGH

Part I

What is Data-Driven Storytelling?

in space. We expect *TabletAR* to perform slower and potentially less precisely than *ImmersiveAR* due to the missing stereoscopic perception required for proper eye-hand coordination.

- $H_{training}$: *We expect participants to become both faster and more precise with increased familiarity over several days in the ImmersiveAR environment.* We assume that participants are well trained on the *Desktop* and that participants will get used to the *TabletAR* environment relatively quickly compared to *ImmersiveAR*.

4.5 Participants

We recruited 15 participants from the University's mailing list. 7 participants were undergraduates enrolled in an architecture program or related and were well trained in the usage of 3D CAD software on a traditional desktop. Four students were enrolled in a computer science program and well trained with mouse and keyboard interactions. Eight participants were male, seven were female. Two participants had previous experience with immersive VR technology and another two had previously used the HoloLens for a short time. Because the device is relatively new, our participants were novices with the HoloLens while all of them were well versed using the desktop. We do believe this reflects a typical scenario until wearable AR devices become truly ubiquitous. Yet, we were particularly interested in participants used to 3D visualization as immersive environments would be of special use to such users.

4.6 Procedure

We followed a full-factorial within-subject study design and blocked participants by environment. While environments were balanced using a Latin square (3 groups), task order was fixed to *distance*, *cluster*, *selection*, and *cuttingplane*. We decided on this order to increase perception and interaction complexity with each task. We report performance measures for each task individually.

Each condition (environment × task) started with 3 non-timed training trials followed by 6 timed study trials. Participants were told to be *as fast as possible*. Tasks were explained by the instructor using text instructions and examples printed on paper. During training, the instructor made sure participants correctly understood the task and could perform the required interactions to solve and finish the task. For each environment (*Desktop*, *TabletAR*, *ImmersiveAR*), the instructor explained the technology and helped participants with setting up.

During each of the 9 trials (including training) we measured task-accuracy and task-completion time from the start of the trial until the trigger event. We tracked positions of the visualization and the camera as well as the relative rotation between them. When participants clicked the trigger button to end a trial, an answering menu was brought up. In *Desktop* and *TabletAR*, the answer menu was shown in the center of the screen. In *ImmersiveAR*, the menu was shown always on the same wall in the study room for all participants, tasks, and trials. Participants were told to first issue the trigger—and hence stop the timer—and then turn to the menu to specify their answer.

Participants could take breaks between trials whenever the timer was not running. In *ImmersiveAR*, the instructor reminded participants to take breaks. Breaks could be taken as long as necessary in all conditions. The study was conducted in a quiet and well illuminated room with enough space for participants to freely walk around the hologram if desired. After the study, we asked each participant to fill out a questionnaire, indicating for each environment the participant's comfort and fatigue, the interaction's ease-of-use, as well as how each of the display conditions supported or hindered the tasks.

4.7 Long-term Training Condition

A random subset of 6 (out of 15) of the study participants was invited for a special condition to study the effects of familiarity/training on *ImmersiveAR* performance. Participants came back to the lab for 5 consecutive days to only perform the *ImmersiveAR* condition. Tasks, task order, and task difficulty remained the same. However, we generated new data for each session and for each of the 9 trials using the methods described in Sect. 4.3. On average, participants spent 15-20 minutes on the *ImmersiveAR* condition each day. We report the results of this *long-term training* group separately in Sect. 5 and Sect. 6.

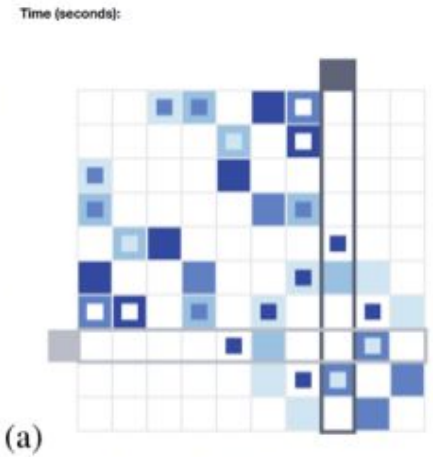


Fig. 7. Results for *time* (seconds), *error*, and subjective reported precision (5-point Likert scale) by task. Confidence intervals indicate 95% confidence for mean values. Dashed lines indicate significances for $p < .05$. Highlighted bars indicate significant best results.

5 Results

We now report on the results of our user study with respect to time, accuracy, user strategies, and subjective user feedback.

5.1 Task Completion Time and Accuracy

On average, it took each participant 1.5 hours to complete the study on all three environments. For each of the 4 tasks, we obtained 270 recorded trials (15 participants × 6 trials × 3 environments), excluding the 3 training trials per condition. We found time and error to not be normally distributed and we were not able to correct to normal distribution through logarithmic or any other transformation. To find outliers, we hence visualized the individual distributions of values for both *time* and *error* for all tasks and environments. Some of these outliers were quite extreme and we decided on above 60 seconds and below 1 second to be good thresholds for removing outliers. In total, we found 19 outlier trials across all tasks. Trials taking longer than 60 seconds may have resulted from technical problems, such as clicker malfunction; trials below 1 second were attributed to accidental clicks ending the trial early. The distribution of outliers per technique was as follows: *Desktop*=2, *TabletAR*=6, *ImmersiveAR*=11. By removing outlier trials, we obtained an unequal number of trials and used the non-parametric Friedman-Chi-Square test for null-hypothesis testing, as well as Mann-Whitney-U test for pairwise significance testing.

Significance values are reported for $p < .05$ (∗), $p < .01$ (∗∗), and $p < .001$ (∗∗∗), respectively, abbreviated by the number of stars in parenthesis. Numbers in parentheses indicate mean values in seconds (time) and mean-errors in the specific unit for each task. Results for time and error are shown in Fig. 7. Confidence intervals indicate 95% confidence. We report time and error measures for each task separately.

Distance: We found significant (∗∗∗) differences for *time*. *Desktop* (7.8s, SD=4s) was found to be faster (∗∗∗) than both *TabletAR* (12.9s, SD=9.1s) and *ImmersiveAR* (12.9s, SD=9.4s). For *error*, Friedman-Chi-Square test did not find significant differences. However, the pairwise comparison with Mann-Whitney-U test revealed *Desktop* (.09, SD=.3s) to be more precise (∗) than *TabletAR* (.18, SD=.4s). No significant difference was found between *ImmersiveAR* (.13, SD=.3s) and *TabletAR* (.18, SD=.4s), though *ImmersiveAR* was slightly faster than *TabletAR* on average. We thus can fully accept $H_{distance-time}$ but have to reject $H_{distance-error}$ due to the lack of significance. We conclude that users were faster *and* more accurate with *Desktop*, confirming earlier findings [60].

Clusters: We found significant differences (∗∗∗) for *time*, with *Desktop* (9.2s, SD=5s) being the fastest (∗∗∗) (*ImmersiveAR*=17.2s, SD=11s, *TabletAR*=16.2s, SD=9s). We can thus fully accept $H_{cluster}$. The time difference is likely due to the time required to physically move one's head or the marker. For *error*, Friedman-Chi-Square test found a significant effect of the task (∗∗). Pair-wise comparison with Mann-Whitney-U test found *Desktop* (.16, SD=.4) and *ImmersiveAR* (.16, SD=.4) to be more precise (∗∗) than *TabletAR* (.33, SD=.5). This result came as a surprise. Since *TabletAR* featured components of the two other environments (monoscopic display and marker interaction) we attribute the increase in precision to the ease and precision in rotation in *Desktop* and stereoscopic vision coupled with head-movement in *ImmersiveAR*.

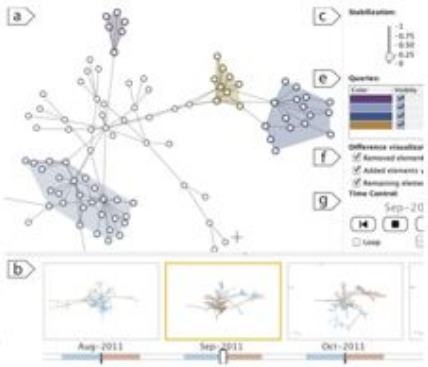
Selection: We found highly significant differences (∗∗∗) between all environments for *time*. *ImmersiveAR* (19.7s, SD=9s) was slowest (∗∗∗) while *Desktop* (6.7s, SD=3s) was fastest and significantly (∗∗) faster than *TabletAR* (8.6s, SD=4.7s). We thus have to reject $H_{selection}$. We attribute the lack of speed of *ImmersiveAR* to the time required to move one's head and body around the visualization. For *error*, we found *TabletAR* (2.7, SD=2.8s) to require more (∗∗∗) clicks (touches) than the other two conditions (*ImmersiveAR*=1.3 (SD=1.7), *Desktop*=1.7 (SD=2)). We attribute this to the fat-finger problem as people can more accurately pinpoint smaller targets with the mouse. This was crucial in the *selection* task where some points were partly hidden and which required rotation of the model and hence added time in *TabletAR*. *ImmersiveAR* required fewer clicks than *Desktop*, indicating that in real 3D space participants could better judge when a marked cube was hit. While the precision of *ImmersiveAR* came at the price of speed, we observed that in *Desktop* participants sometimes interacted too fast and hence missed the respective targets.

Cuttingplane: We found significant differences (∗) for this task with respect to *time*. *ImmersiveAR* (18.6s, SD=11s) was faster (∗∗) than both *Desktop* (22.2s, SD=13.4s) and *TabletAR* (27.7s, SD=17s). For *error*, we found a trend towards significance ($p = .056$) for *Desktop* (22.7, SD=14.2) being less precise than *ImmersiveAR* (21.9, SD=13.8). We can thus accept $H_{cuttingplane}$, but state that generally high precision is possible in all three environments.

5.2 Interaction and Task Strategies

We were interested in participants' exploration of different strategies and affordances of the visualization environments, especially for *ImmersiveAR*. We did not force participants into a single strategy, e.g., to remain seated and rotate the marker. For *ImmersiveAR*, only 2/15 (13.3%) remained seated during all tasks, while the rest (86.6%) stood up after the first training trial and locked holograms in free space (air-lock in Fig. 1(a,c-d)). More than half of the participants (8/13) placed the visualization at the height of their head and eyes, while the others (5/13) placed the visualization hologram at the height of their chest, i.e., lower than head height. For *cluster*, participants reported on the convenience of moving themselves or their head around the air-locked hologram to observe it from all three orthogonal directions. One participant explicitly reported that she placed the visualization so that she faced all orthogonal directions to an equal extent, effectively reducing her time to move around it.

During *TabletAR*, only 2/15 (13.3%) participants stood up and moved the tablet around the visualization or the marker, while the rest remained seated and instead moved the marker. One observed problem during the *TabletAR* condition was that the distance between the marker and the screen had to be large, making viewing the tablet screen for some participants hard. The prevalent strategies for *Desktop* were fast rotation of the visualization (71%), while 35% of the participants also or exclusively rotated slowly.



we found was for *TabletAR* in the *selection* task; participants reported high precision but in fact produced many clicks that did not target the marked points in the visualization. For the same task, however, *ImmersiveAR* was reported to be less precise than *Desktop*, though the recorded data indicated precision as high as for *Desktop*.

ImmersiveAR, understandably, was reported to be difficult to handle in the beginning but became more usable (*"I became accustomed to it in the end"*). The condition was also reported to be an attractive experience. Participants liked the spatial freedom and walking around (*"[I] loved the ability to walk around an object"*). They also positively reported on the stereovision (*"The hololens gives an instant understanding of depth [...]"*,*"ease with which I could judge distances/location"*, *"could see the space clearer"*), and spatial comprehension (*"comprehension was the highest with HoloLense* (SIC)*"*). However, interaction was more cumbersome (*"was very difficult to interact with."*, *"it's good as an experience but harder to for certain things beyond seeing, such as touching or slicing"*). One participant noted though she was prone to motion sickness, she did not feel any symptoms with the *ImmersiveAR*.

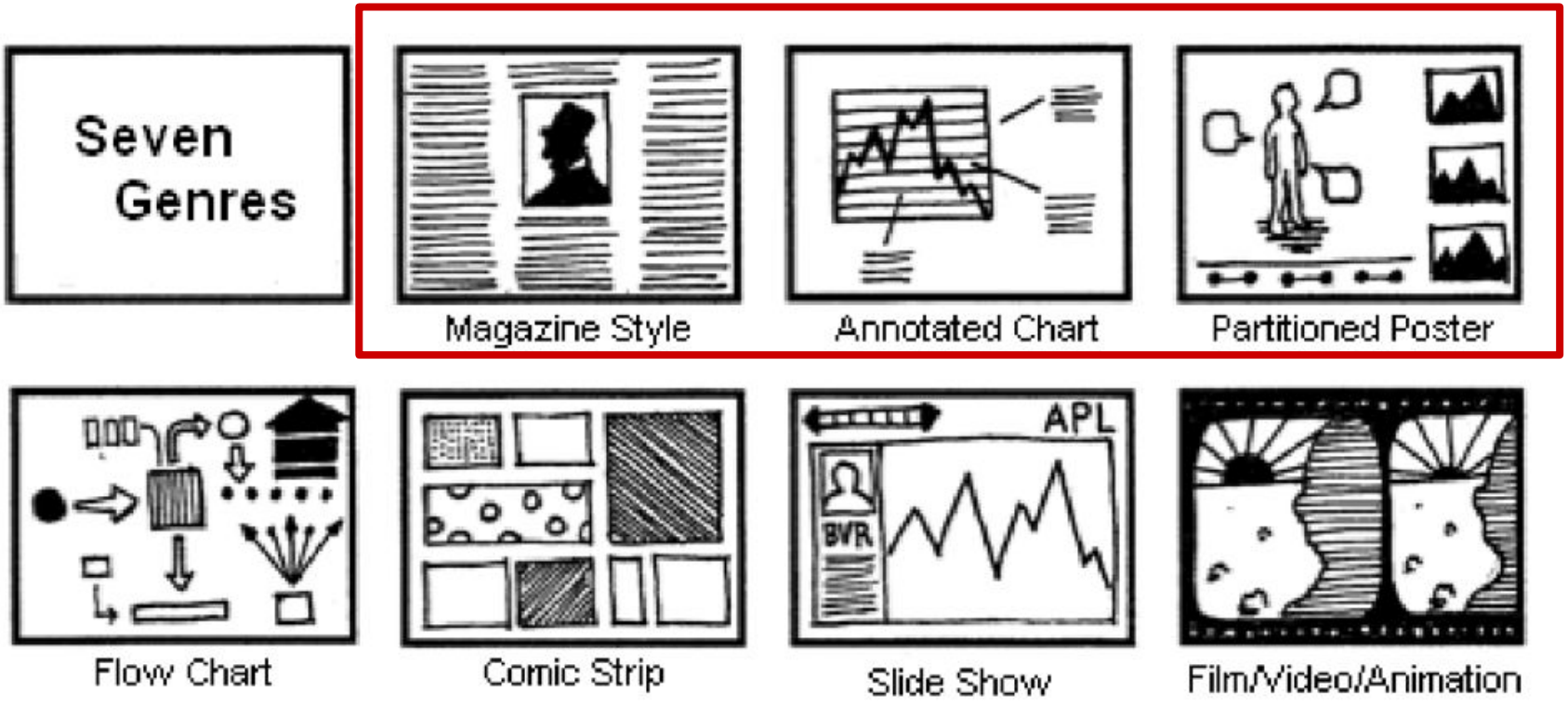
In *TabletAR* participants appreciated the easy and fast selection on the screen, but disliked the spatial mismatch between interaction and perception. One participant reported *"I felt constrained by the positioning of the camera in relation to the hologram markers. That could have been alleviated by moving the tablet just slightly but I didn't want to risk losing view of the marker"*. Others reported on the difficulty of manipulation *"holding tablet in hands contribute to imprecise manipulation."*, *"holding the tablet and markers involves a bit too much simultaneous manipulation to feel very precise."*. One participant suggested dragging objects on the screen, a setting common in other applications (e.g., [37]). In neither *TabletAR* nor *ImmersiveAR*, did the participants report complaints about the markers' patterns distracting them from the task or resulting in any visual interference with the visualization.

For *Desktop*, participants appreciated the ease and effectiveness of the environment (*"easier to complete [the tasks] on the flat screen"*, *"absence of Z parameter"*, *"the best interaction experience was with desctop* (SIC)*"*.) One participant summarized his/her experience as follows: *"To sum it up, Hololense* (SIC) *gives the best comprehension, Desctop* (SIC) *gives the best manipulation."*

5.4 Long-Term Training

To understand the effect of training for the *ImmersiveAR*, we analyzed the four additional sessions for the long-term training group (6 participants). Training was performed once a day, at the same time, for the four days following the participant's first session with the *ImmersiveAR*. We analyzed each task, data set, and participant individually as we believed there would be differences between participants. In particular,

Seven Genres by Segel & Heer



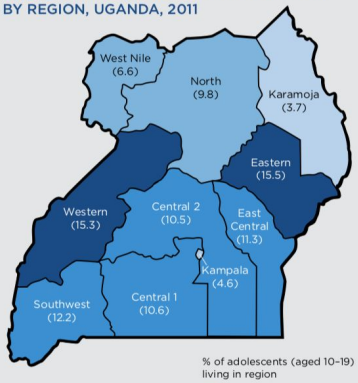
Segel, E., & Heer, J. (2010). Narrative visualization: Telling stories with data. *IEEE transactions on visualization and computer graphics*, *16*(6), 1139-1148.

Magazine Style

physical, social, political, and economic structures of a region can place residents at varying risks for vulnerability. Areas susceptible to violence or natural disaster pose clear threats to individuals. An individual's environment also affects his or her development and behavioral choices. Resources available in the physical and social environments create the contexts within which decisions are made about health, education, and employment. Political and social environments also dictate whether resources are accessible to all adolescents. An examination of the residential distribution of adolescents provides a baseline for comparing geographical patterns of vulnerability. Within Uganda, by type of residence, the majority of adolescents (87 percent) live in rural versus urban areas. Figure 6 shows the distribution of adolescents aged 10 to 19 living in Uganda. Regional distributions show Karamoja contains only four percent of the adolescent population. Kampala with a much denser population contains 4.6 percent of the population. The Eastern and Western regions contain the largest proportions of the adolescent population.

FIGURE 6

PROPORTION OF ADOLESCENTS AGED 10-19 BY REGION, UGANDA, 2011



Source: DHS 2011.

Household factors influencing vulnerability

Household-level factors have direct impacts on the well-being of adolescents. Households are the primary setting where adolescents live and engage in activities. For this reason, the household environment and the people who live there have significant impacts on the lives of adolescents. Physical conditions of the home influence the health of residents. Family structures and demographic characteristics of household members affect the knowledge, decisions, behaviors and interactions in the environment of the adolescent.

Access to improved water sources and sanitation

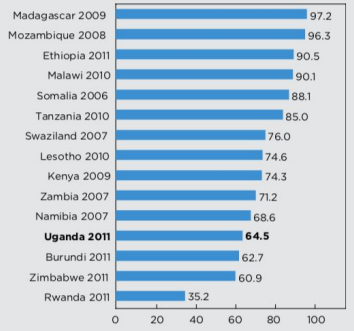
Unsafe water, inadequate sanitation, and poor hygiene are among the five leading risk factors responsible for one quarter of all deaths in the world (WHO 2009). Unsafe water supplies and inadequate sanitation in homes increase exposure to water-borne diseases and can cause diarrhea. Ensuring access to clean water sources and sanitation is key to maintaining hygiene and health. Improved water sources are those that either naturally protect water from contamination or are constructed to do so. These include piped water, public taps, standpipes, boreholes, tube wells, protected wells and springs, and rainwater collection. Improved sanitation includes constructs and systems that prevent fecal contamination. These include flush or pour toilets, ventilated pit latrines, pit latrines with slabs, and composting toilets (UNICEF 2013b).

Housing conditions across East and Southern Africa are largely in need of improvement, and lack of improved sanitation varies by country. In nearly all of East and Southern Africa, over half of adolescents either do not have improved sanitation or share facilities with other households. Conditions are worst in Madagascar and Mozambique where fewer than four percent of adolescents live in households with improved sanitation that is not shared (Figure 7). Rwanda has the lowest proportion of adolescents affected—35 percent—which is still unacceptably high. Lack of access to improved water sources affects lower proportions but is still a problem in the region. In five countries, fewer than half of adolescents have access to improved water sources (Figure 8). Water conditions are best in Namibia, where only 15 percent of adolescents have no access to improved water.

In Uganda, overall access to improved water and sanitation increased by a small but significant percentage between 2006 and 2011 (Figure 9). In 2006, 33 percent of adolescents had no access to improved water; in 2011, it is 30 percent. The proportion of adolescents without access to improved

FIGURE 7

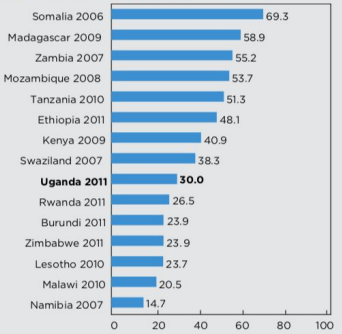
PERCENT OF ADOLESCENTS AGED 10-19 LIVING IN HOUSEHOLDS WITH NO IMPROVED OR WITH SHARED SANITATION, EAST AND SOUTHERN AFRICA



Source: DHS 2007-2011; MICS 2006-2008.

FIGURE 8

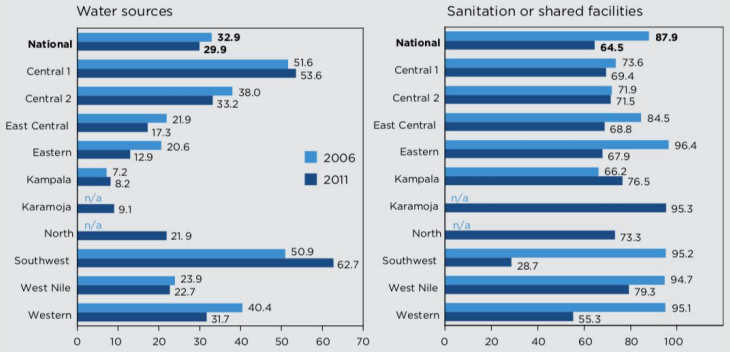
PERCENT OF ADOLESCENTS AGED 10-19 LIVING IN HOUSEHOLDS WITH NO IMPROVED WATER SOURCE, EAST AND SOUTHERN AFRICA



Source: DHS 2007-2011; MICS 2006-2008.

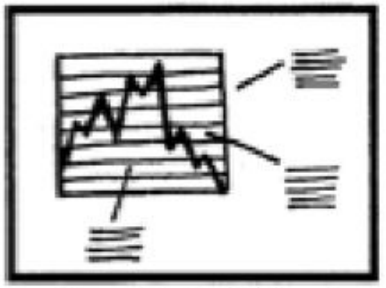
FIGURE 9

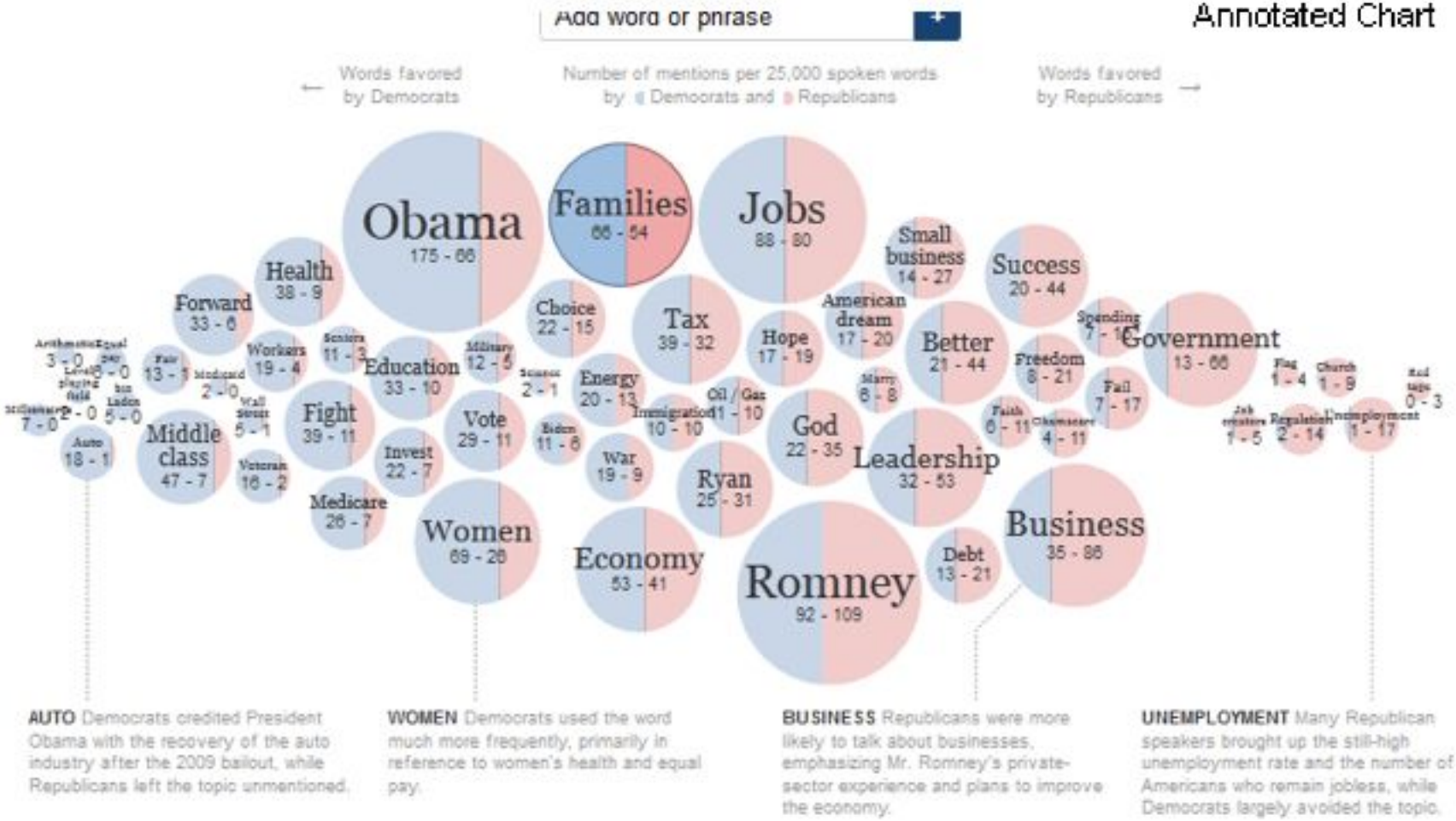
PERCENT OF ADOLESCENTS AGED 10-19 LIVING IN HOUSEHOLDS WITHOUT ACCESS TO IMPROVED WATER AND WITHOUT ACCESS TO IMPROVED OR WITH SHARED SANITATION, IN UGANDA, BY REGION, 2006 AND 2011



Source: DHS 2006 and 2011.
Note: Changes to the geographic boundaries were made to the North region in the 2011 DHS. The 2006 DHS North region is now divided into the North and Karamoja. For this reason, rates for 2006 are not shown for the North since it is not comparable and Karamoja was not identified in the previous survey.

Annotated Chart





Partitioned Poster *(Infographic)*

Partitioned Poster

https://www.visualcinnamon.com/portfolio/baby-spike

GRAPHIC SCIENCE

The Average 7.3 babies born per minute

Eat First
More births of all types occur right after lunch

Day Shift
Births peak around 8 A.M., then rise again between noon and 1 P.M. Hospitals typically have more doctors and nurses on hand during the morning and fewer later in the day.

Babies Born by Minute

Boom
The morning peak is driven by planned C-sections

The Baby Spike

Births peak on weekdays during daytime work hours

Two generations ago babies were born pretty much spontaneously, around the clock. But today in the U.S., about half of all births are cesarean sections prescheduled by Mom or deliveries induced by doctors concerned about the mother's or baby's health. These medical procedures have skewed the days of the week, and hours of the day, during which those little bundles of joy arrive.

The procedures dominate because more than 98 percent of infants are born in a hospital, despite what seems to be the rising popularity of home births. Far more babies now arrive on weekdays than on weekends, most between 8 A.M. and 6 P.M. "We can't schedule spontaneous labor, obviously," says Neel Shah, a physician and professor at Harvard Medical School. "But we can schedule delivery."

—Mark Fischetti and Zan Armstrong

The Average 447 babies born per hour

Fewest Births
Sunday night between 2 and 3 A.M.

Early Riser
More babies than average are born on weekdays during daylight hours. Fewer are born on weekends or at night, primarily because fewer hospital staffers are on duty, so women tend not to schedule their delivery then. Despite folklore, a full moon has no effect.

Babies Born by Hour

Midday Special
On a typical Tuesday, 770 babies are born from noon to 1 P.M.

The Average 77,000 babies born per week

No, Thanks
Moms do not schedule C-sections around Thanksgiving

Happy Holidays
Babies seem to arrive nine months after Christmas and New Year's Eve

Summer Son
Evidently, more people have sex during colder months, leading to more births nine months later from July through October, and less sex during warmer months.

Babies Born by Week

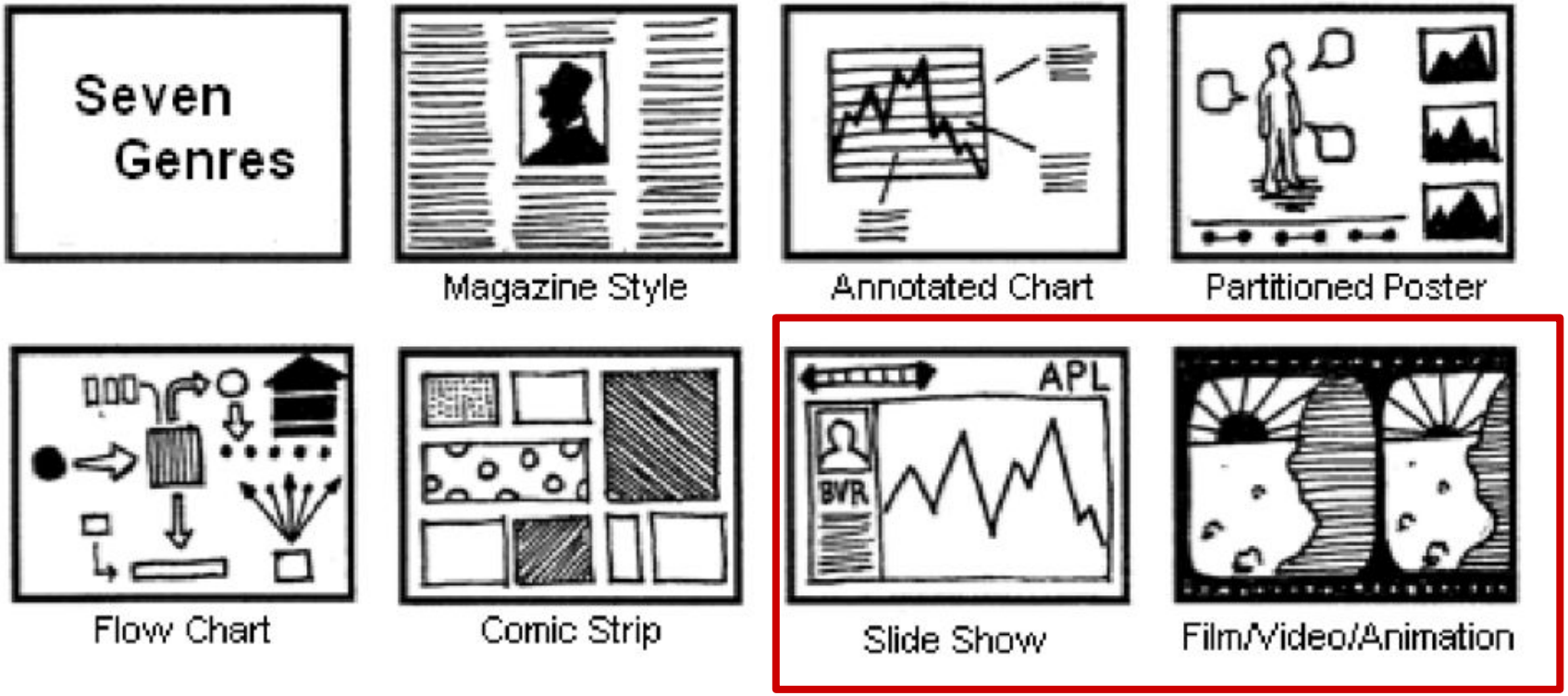
Each graph shows U.S. data averaged across 2014

More than average
25% fewer
25% more
Fewer than average
Zero babies born (center point)
Average number of babies born (yellow line)

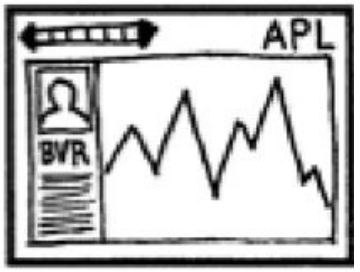
SOURCES: FINETHINGSOUT, FROM DATA SUPPLIED BY U.S. SOCIAL SECURITY ADMINISTRATION [and] CENTERS FOR DISEASE CONTROL AND PREVENTION [minute and hour data]

Graphic by Nadieh Bremer and Zan Armstrong

Slide Shows


Seven Genres
Magazine Style
Annotated Chart
Partitioned Poster
Flow Chart
Comic Strip
APL
BVR
Slide Show
Film/Video/Animation

Slideshow



Slide Show

https://ig.ft.com/sites/climate-change-calculator/

« Back 1/10 Next »

Create your own mod

Annual GHG emissions
(tonnes bn CO_2e)

Global mean temp.
change by 2100 (°C)

140
120
100
80
60
40
20
0

Pathway for 6 °C warming

Pathway for 2 °C warming

6
5
4
3
2

2000 2020 2040 2060 2080 2100

Efforts to cut emissions

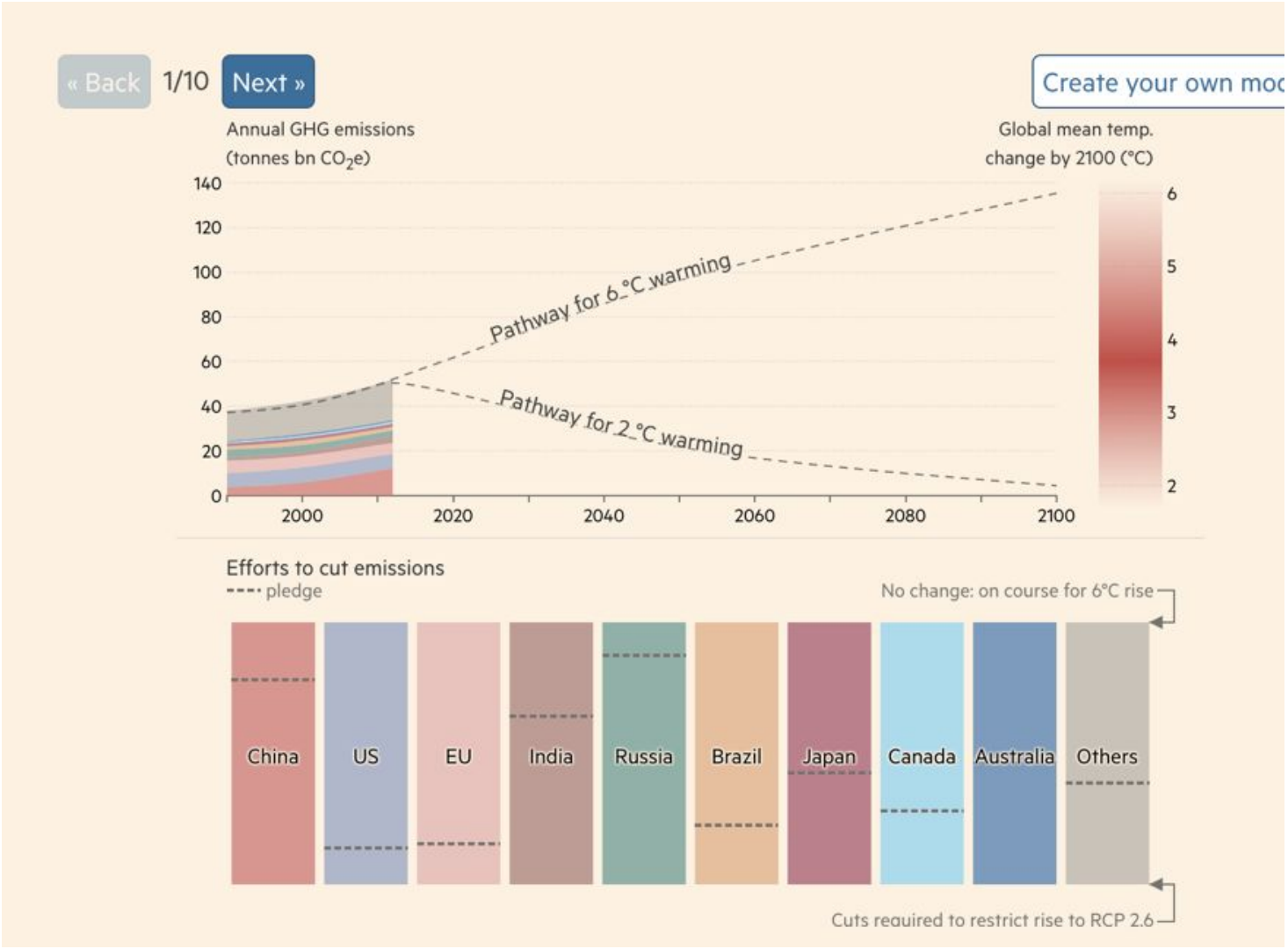
pledge

No change: on course for 6°C rise

China US EU India Russia Brazil Japan Canada Australia Others

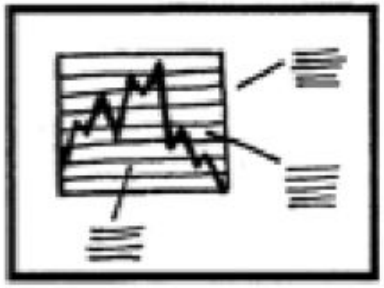
Cuts required to restrict rise to RCP 2.6

Interactive

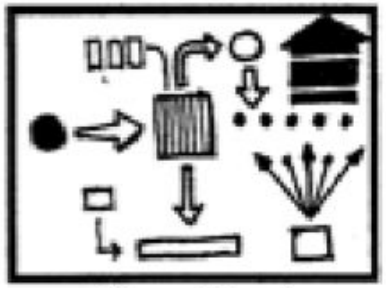


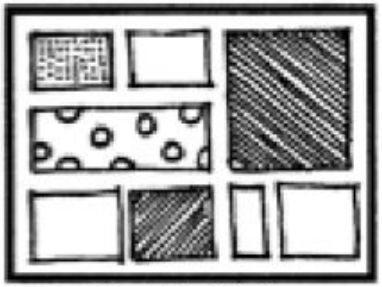
Data Videos

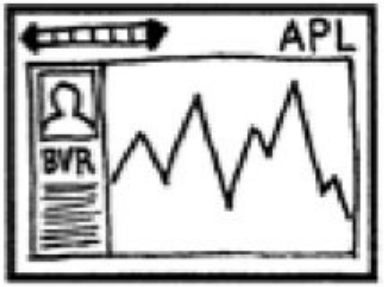

Magazine Style


Annotated Chart

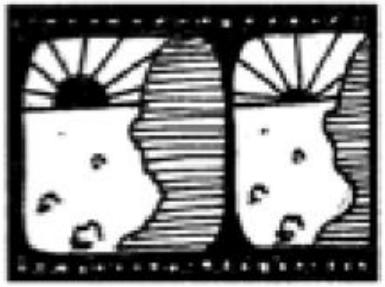

Partitioned Poster


Flow Chart

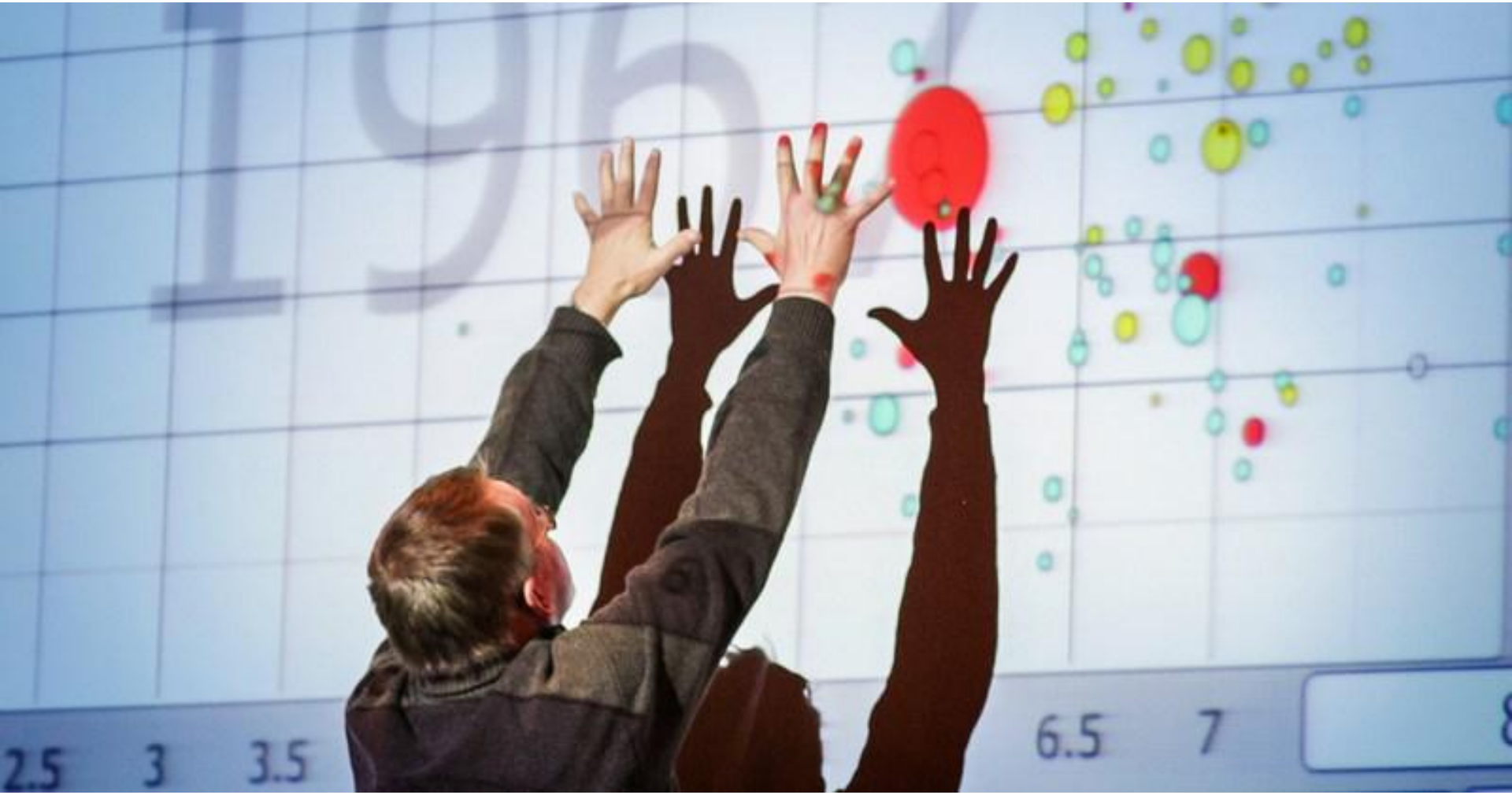

Comic Strip



Slide Show

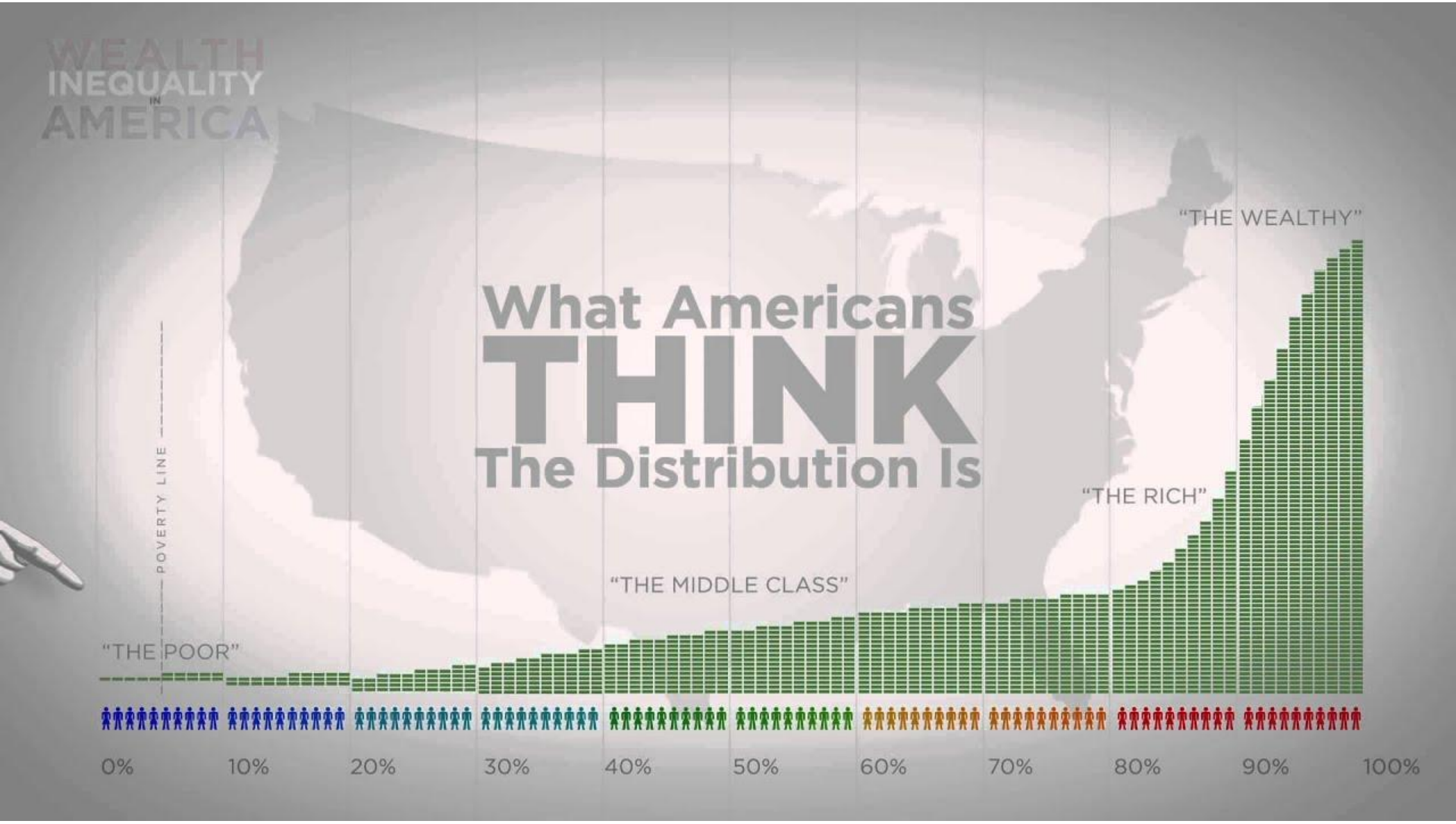

Film/Video/Animation

Life Presentations



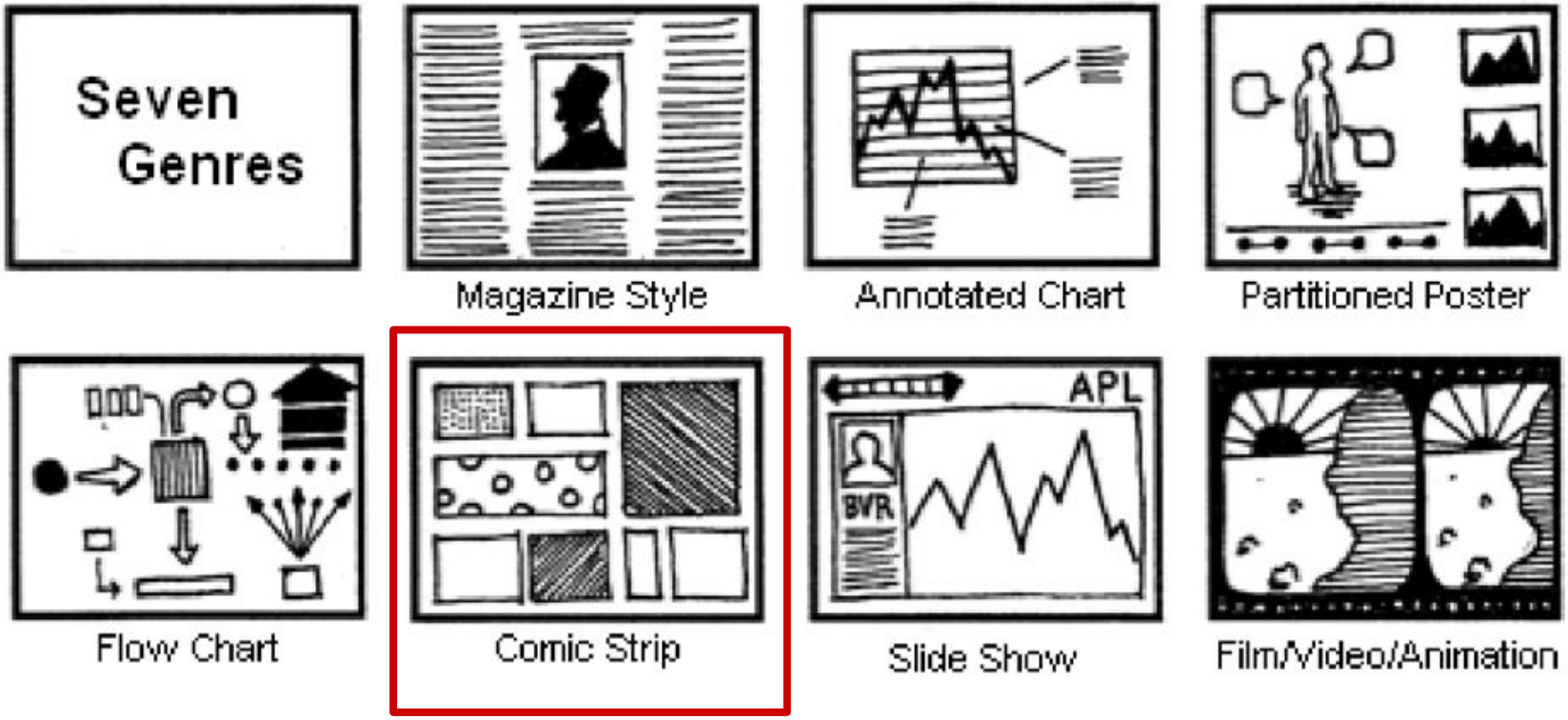
https://www.ted.com/talks/hans_rosling_shows_the_best_stats_you_ve_ever_seen?language=en

Data Videos



https://www.youtube.com/watch?v=QPKKQnijnsM

Data Comics



Bach, Benjamin, Nathalie Henry Riche, Sheelagh Carpendale, and Hanspeter Pfister. "The emerging genre of data comics." *IEEE computer graphics and applications* 37, no. 3 (2017): 6-13.

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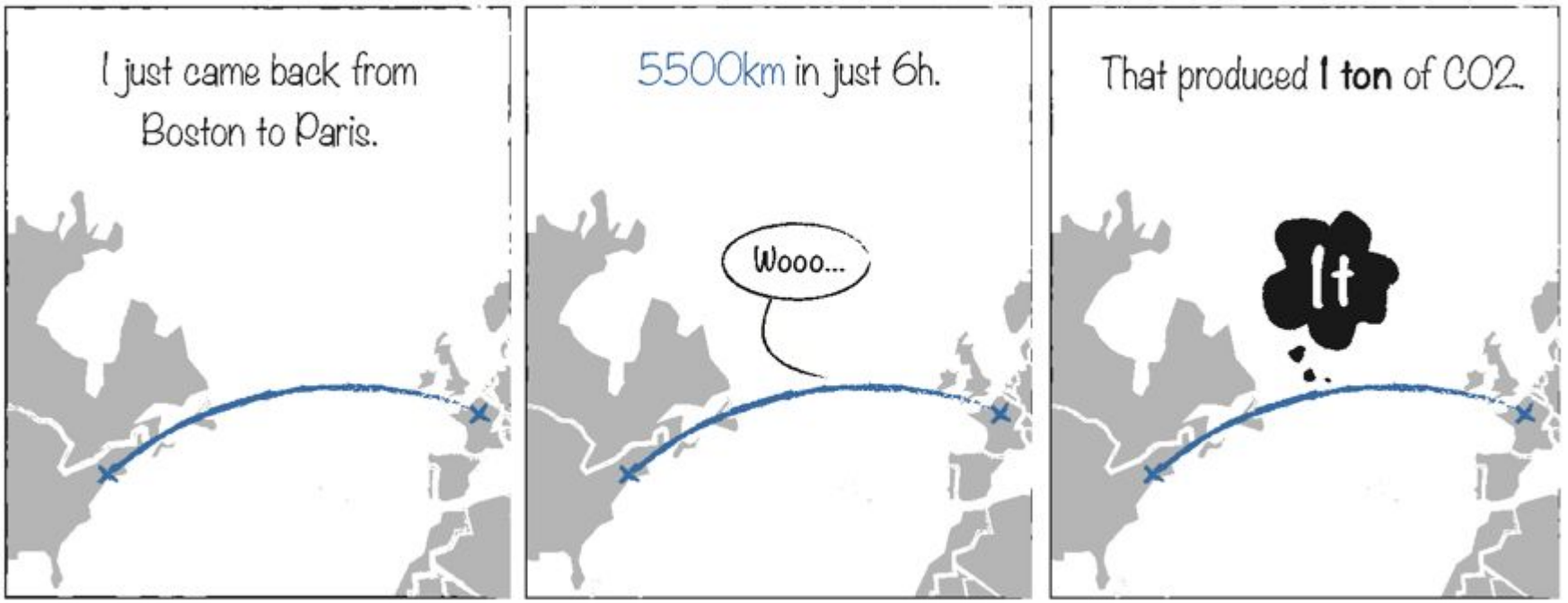
Part II

Data Comics

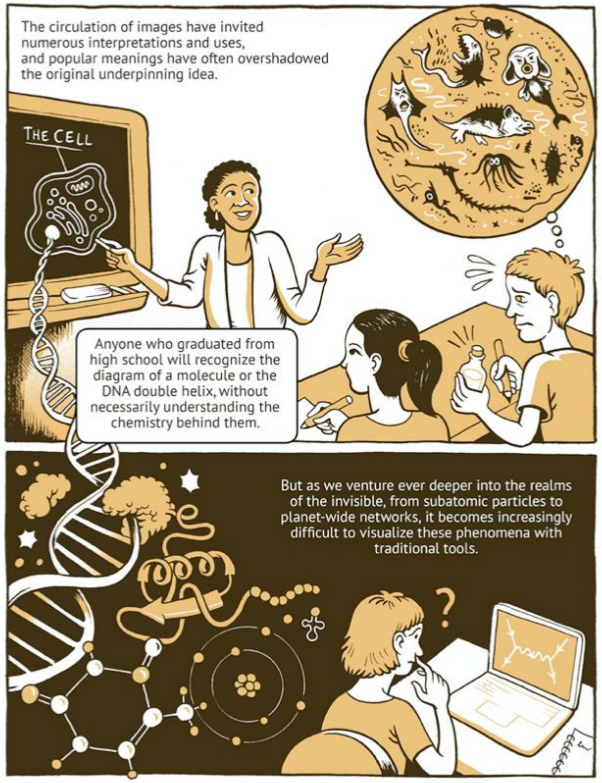
Panel

Panel

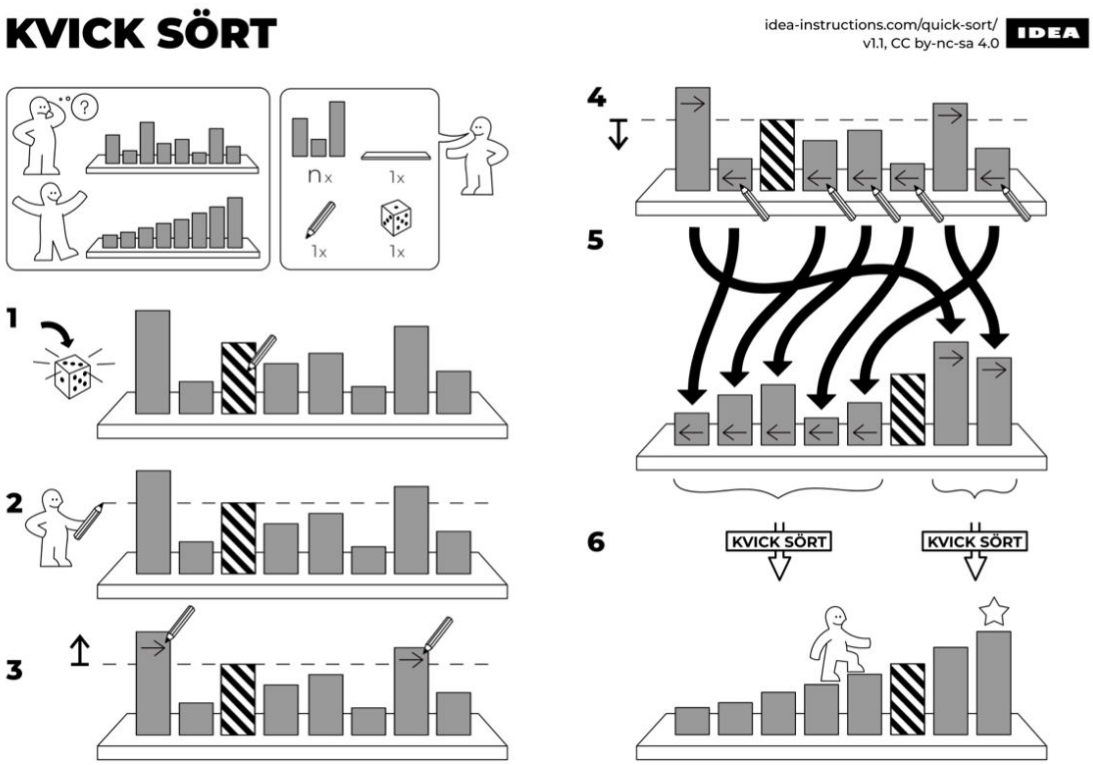


Sequence

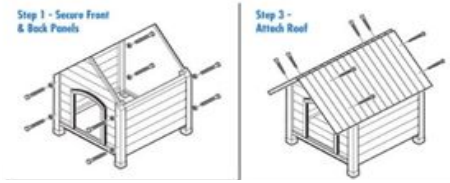
Comics for communication

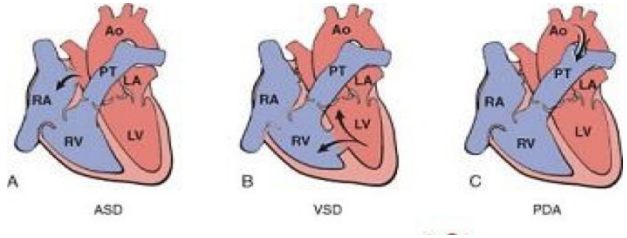


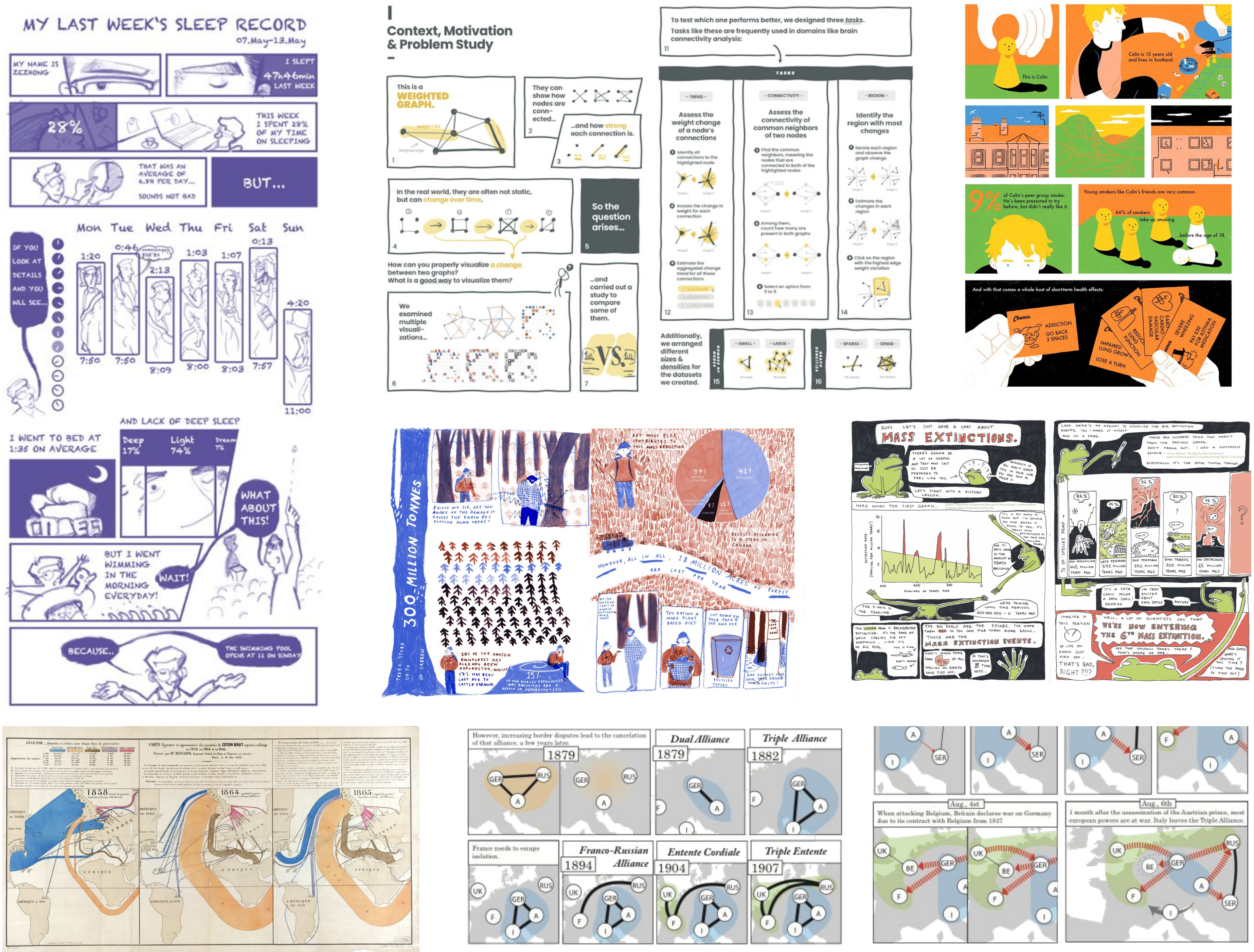
Farinella, Matteo. "Of Microscopes and Metaphors: Visual Analogy as a Scientific Tool." The Comics Grid: Journal of Comics Scholarship 8 (2018).



idea-instructions.com/quick-sort/

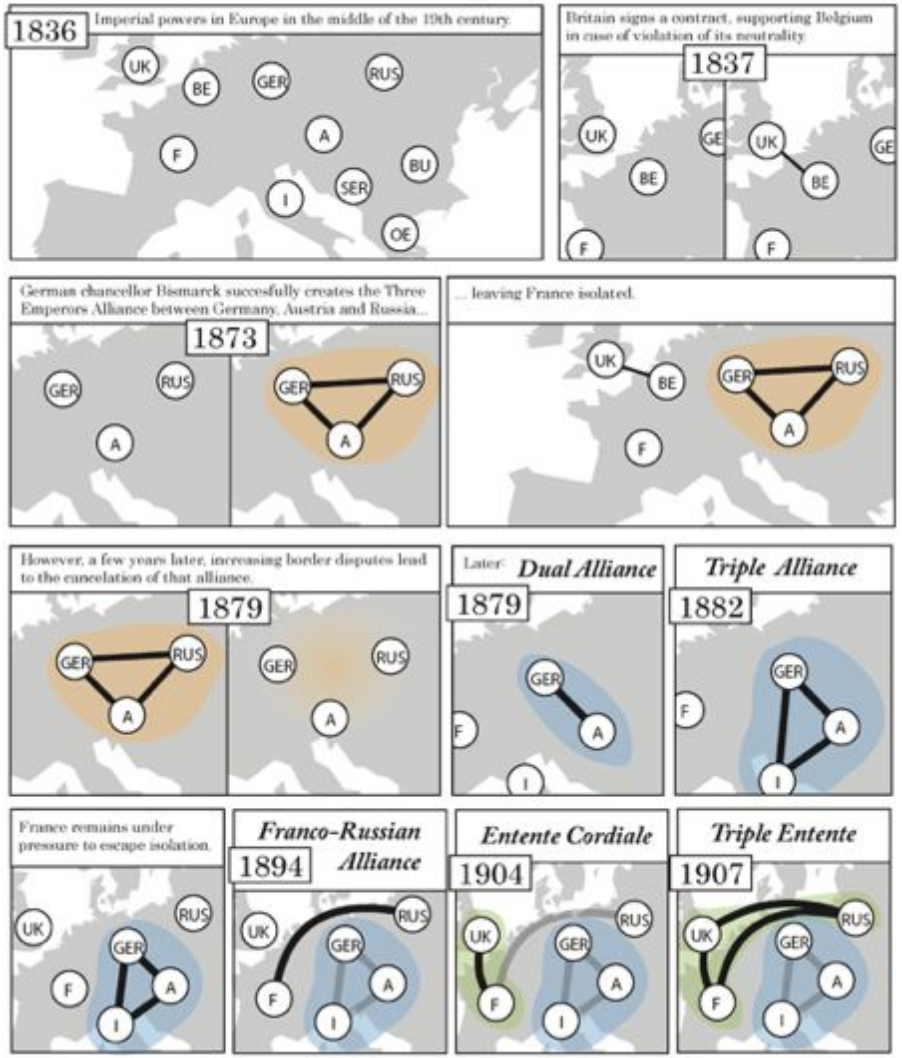


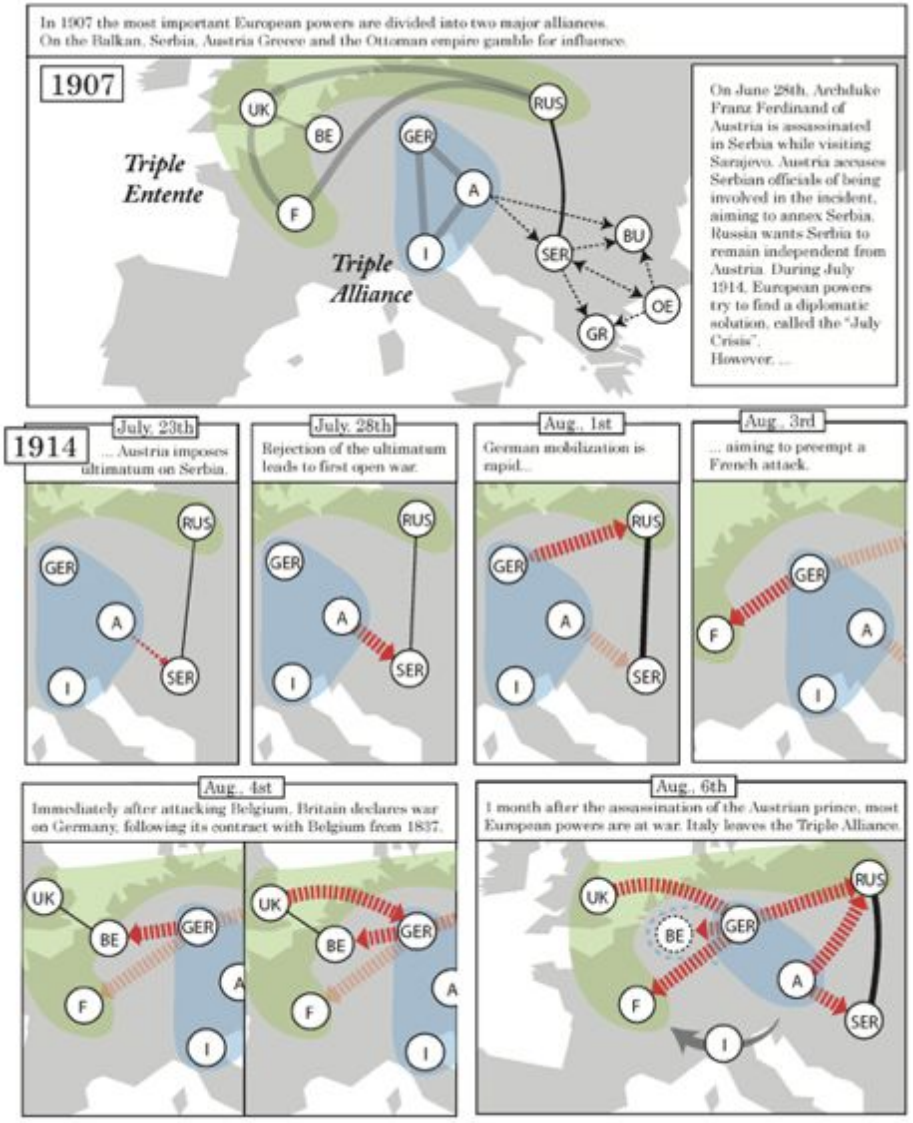




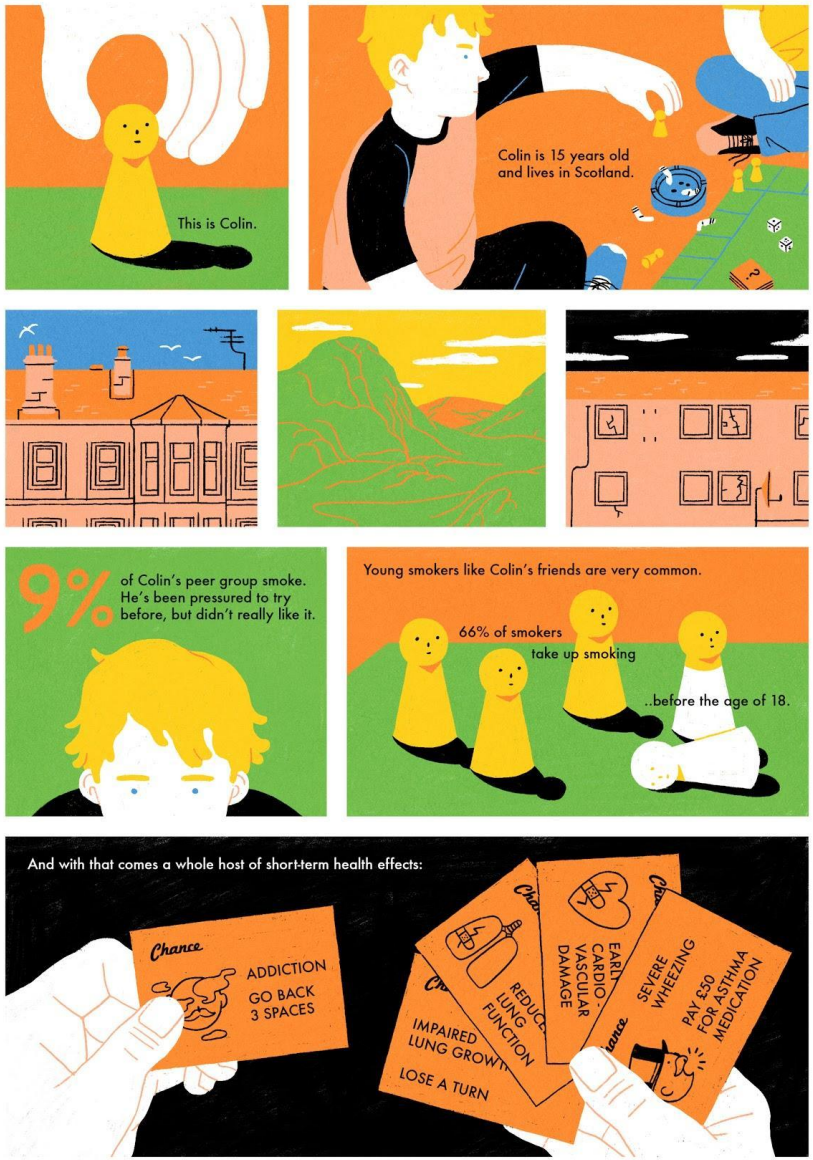
MY LAST WEEK'S SLEEP RECORD
07.May-13.May
MY NAME IS ZEZHONG
I SLEPT 47h46min LAST WEEK
28%
THIS WEEK I SPENT 28% OF MY TIME ON SLEEPING
THAT WAS AN AVERAGE OF 6.8H PER DAY...
SOUNDS NOT BAD
BUT...
Mon Tue Wed Thu Fri Sat Sun
IF YOU LOOK AT DETAILS AND YOU WILL SEE...
I WENT TO BED AT 1:35 ON AVERAGE
AND LACK OF DEEP SLEEP
Deep 17%
Light 74%
Dream 7%
WHAT ABOUT THIS!
BUT I WENT WIMMING IN THE MORNING EVERYDAY!
WAIT!
BECAUSE..
THE SWIMMING POOL OPENS AT 11 ON SUNDAY
Context, Motivation & Problem Study
This is a WEIGHTED GRAPH.
They can show how nodes are conn-ected...
...and how strong each connection is.
In the real world, they are often not static, but can change over time.
So the question arises...
How can you properly visualize a change between two graphs?
What is a good way to visualize them?
We examined multiple visuali-zations...
...and carried out a study to compare some of them.
VS.
To test which one performs better, we designed three tasks.
Tasks like these are frequently used in domains like brain connectivity analysis:
TASKS
TREND
Assess the weight change of a node's connections
CONNECTIVITY
Assess the connectivity of common neighbors of two nodes
REGION
Identify the region with most changes
Additionally, we arranged different sizes & densities for the datasets we created.
SMALL
LARGE
SPARSE
DENSE
This is Colin.
Colin is 15 years old and lives in Scotland.
9%
of Colin's peer group smoke. He's been pressured to try before, but didn't really like it.
Young smokers like Colin's friends are very common.
66% of smokers take up smoking
...before the age of 18.
And with that comes a whole host of short-term health effects:
Chance
ADDICTION GO BACK 3 SPACES
IMPAIRED LUNG GROWTH
LOSE A TURN
300 MILLION TONNES
18 MILLION ACRES OF FOREST ARE LOST PER YEAR
MASS EXTINCTIONS.
HERE COMES THE FIRST GRAPH.
WE'RE NOW ENTERING THE 6TH MASS EXTINCTION.
THAT'S BAD, RIGHT ?!!?
1858
1864
1865
AFRIQUE
However, increasing border disputes lead to the cancelation of that alliance, a few years later.
1879
GER
RUS
A
Dual Alliance
1879
Triple Alliance
1882
France needs to escape isolation.
Franco-Russian Alliance
1894
Entente Cordiale
1904
Triple Entente
1907
UK
F
I
SER
BE
Aug. 4st
When attacking Belgium, Britain declares war on Germany due to its contract with Belgium from 1837
Aug. 6th
1 month after the assassination of the Austrian prince, most european powers are at war. Italy leaves the Triple Alliance.

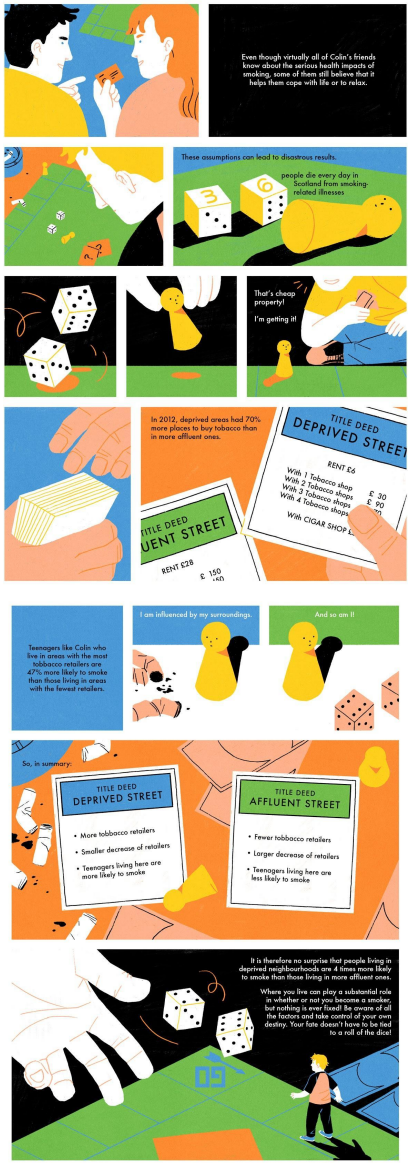
European Alliances before World War I (1836-1914)

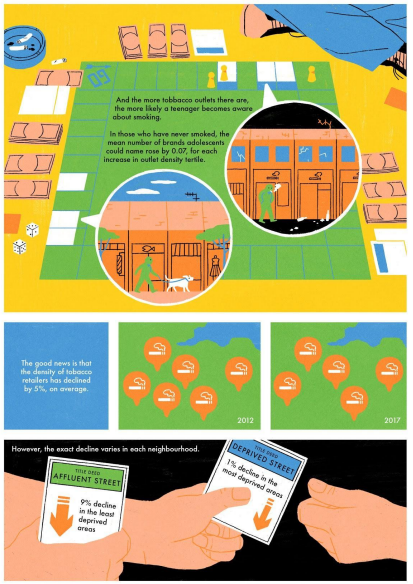




Smoking





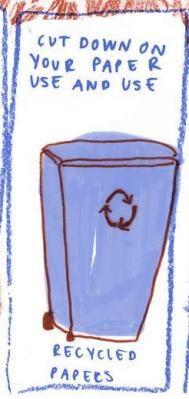


Terri Po

TREES STORE UP TO 300 MILLION TONNES OF CARBON

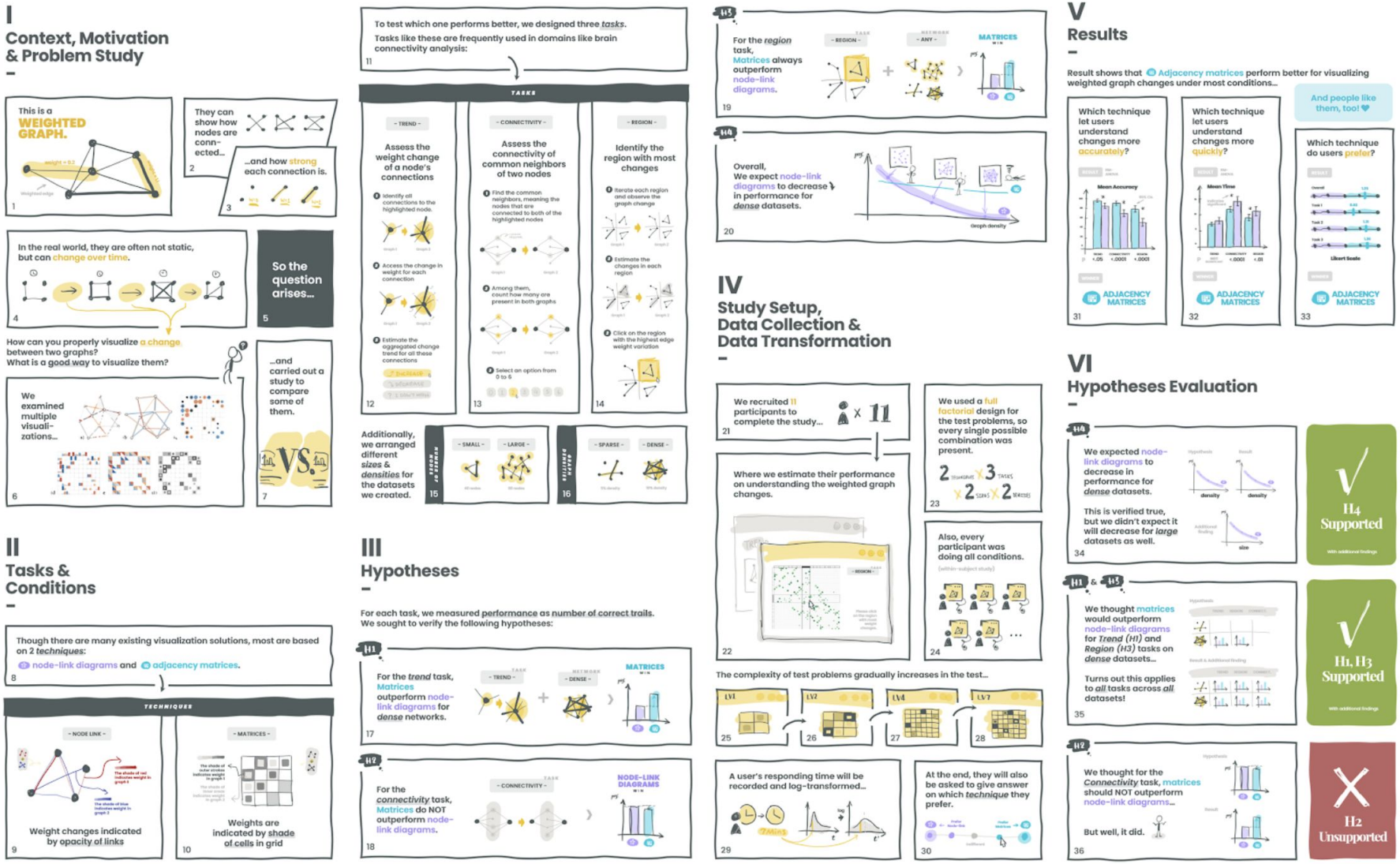
EXCUSE ME SIR, ARE YOU AWARE OF THE DAMAGE IT CAUSES THE EARTH BY CUTTING DOWN TREES?

HOWEVER, ALL IN ALL, 18 MILLION ACRES OF FOREST ARE LOST PER YEAR



Isotype, Arnold Gantz, ~1920

Explaining Data Analysis



Jingtao Chow

https://statscomics.github.io

Wang, Z., Ritchie, J., Zhou, J., Chevalier, F. and Bach, B., 2020. Data Comics for Reporting Controlled User Studies in Human-Computer Interaction. *IEEE Transactions on Visualization and Computer Graphics*.

Data Comics Misunderstandings

- Data comics are **not** about cartoons
  - It's about explanation
  - It's about guidance
  - It's about focus
  - It's about sequence
  - It's about data visualization

- You do **not** have to be an artist
  - It's not about style, it's about content
  - Storyboards

- Data comics do **not** have to fill a book

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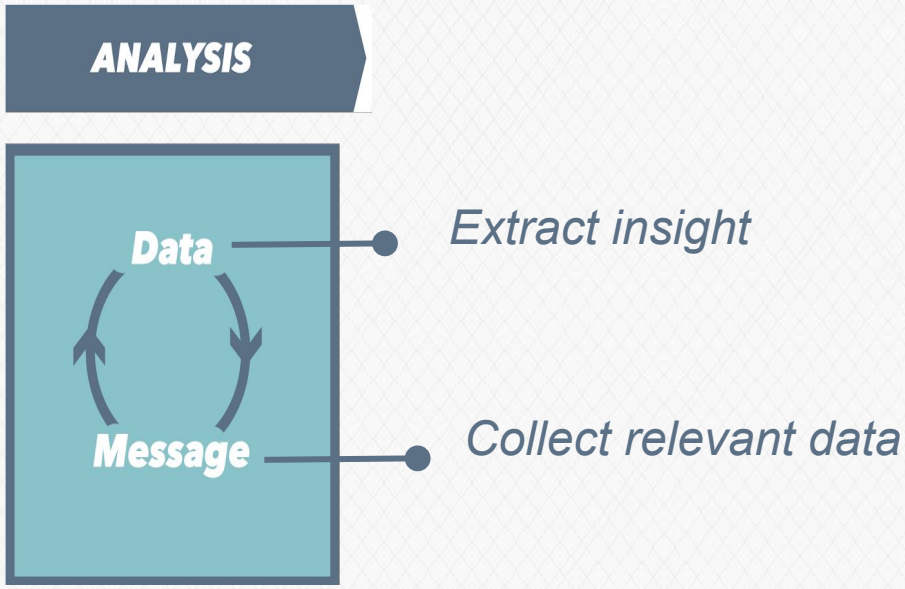
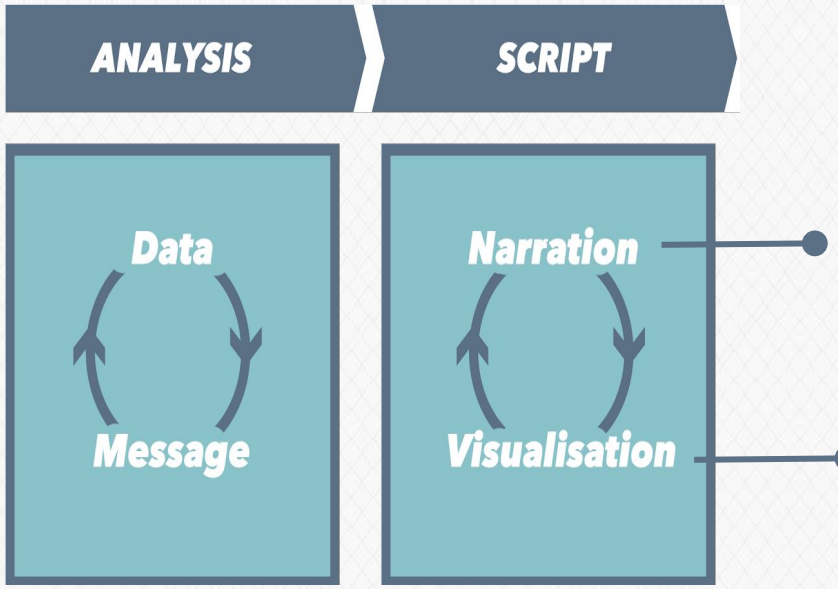
Making Process



Making Process

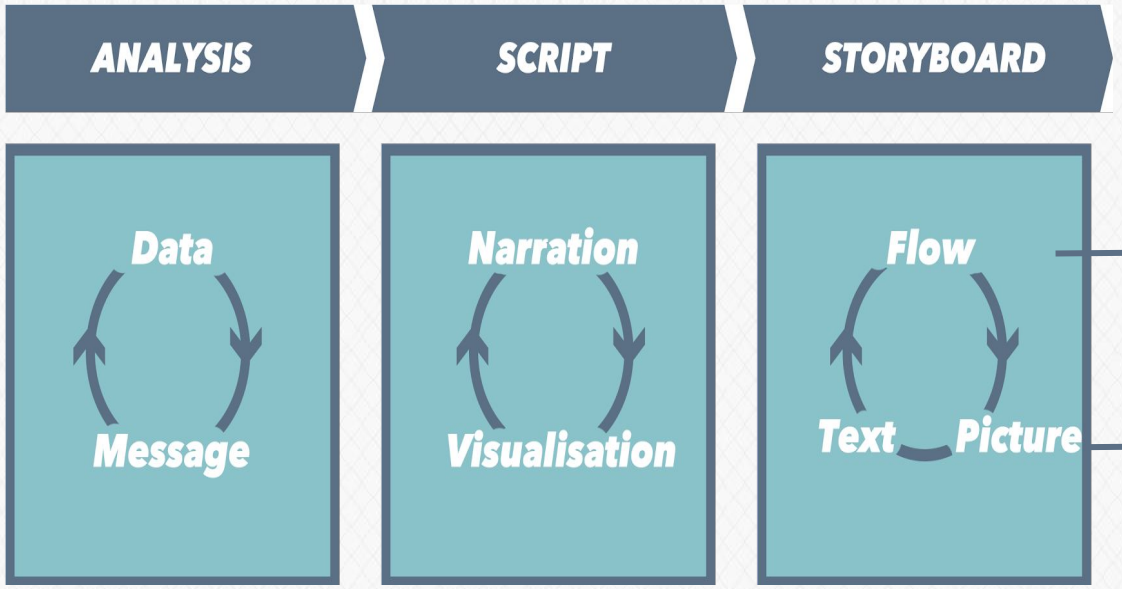


Sequence of messages, arguments and data points

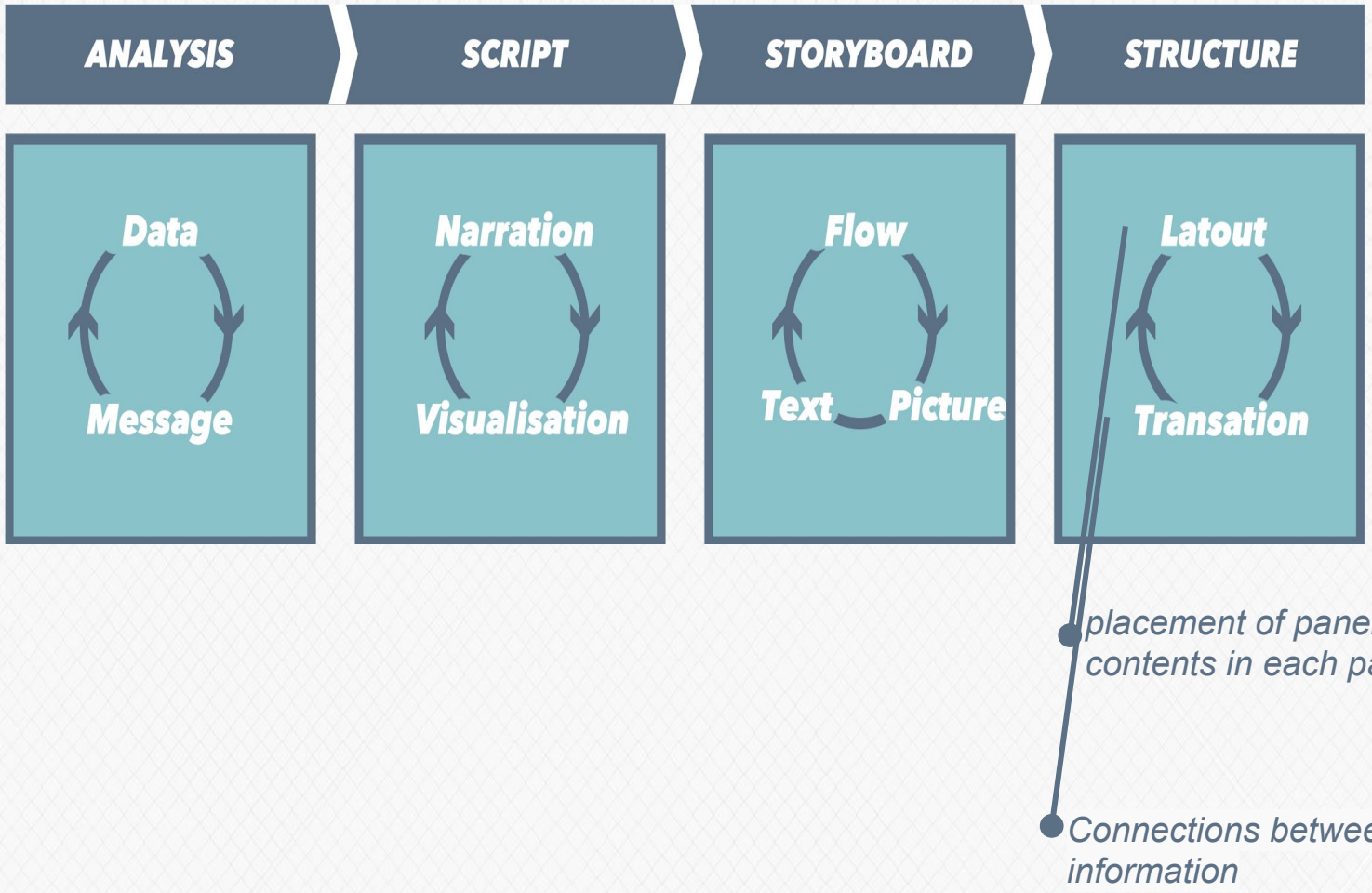
Introduction, middle and end

Visualising the data

Making Process



Making Process



Zezhong Wang & Benjamin Bach

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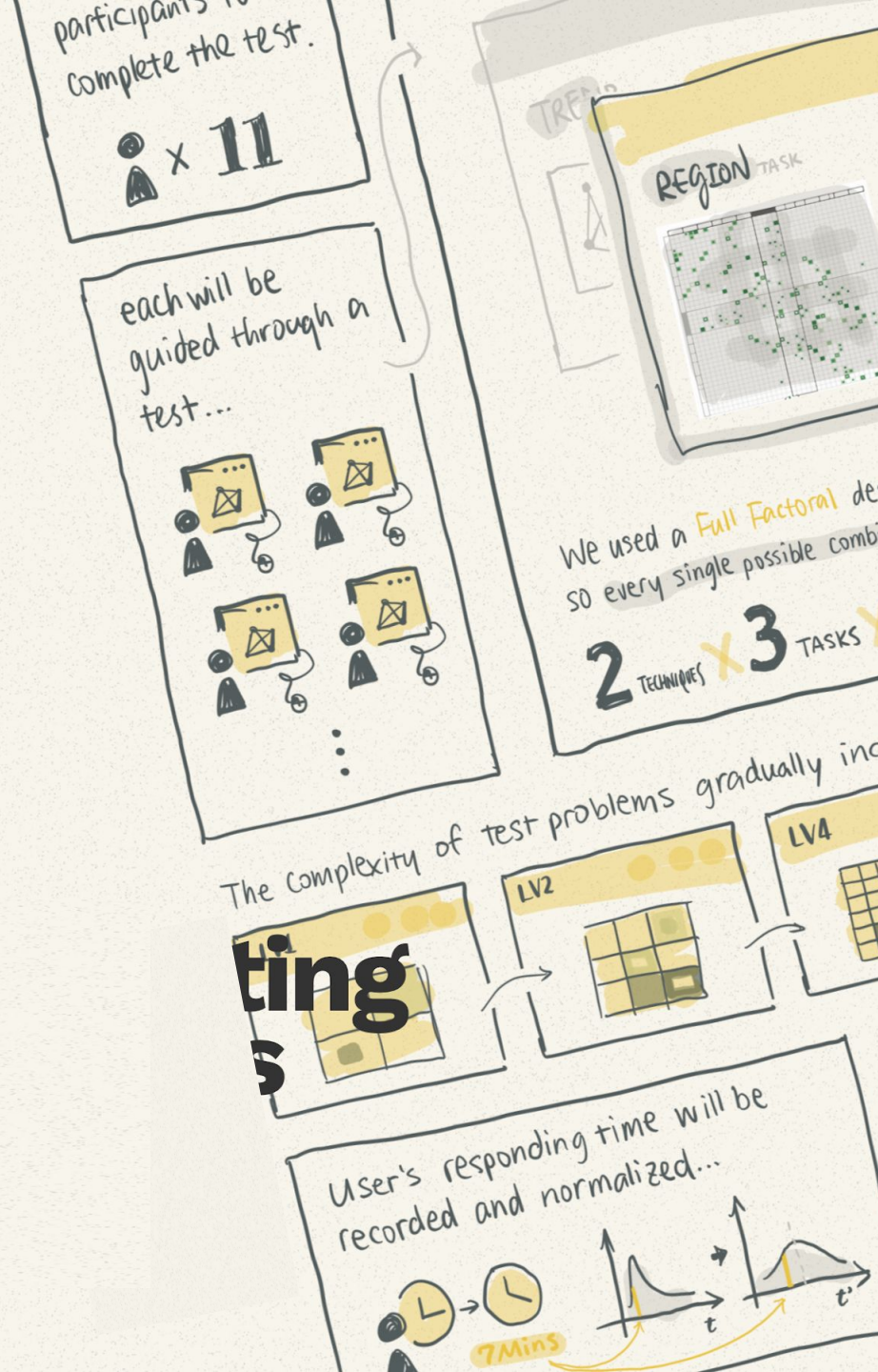
Activity I

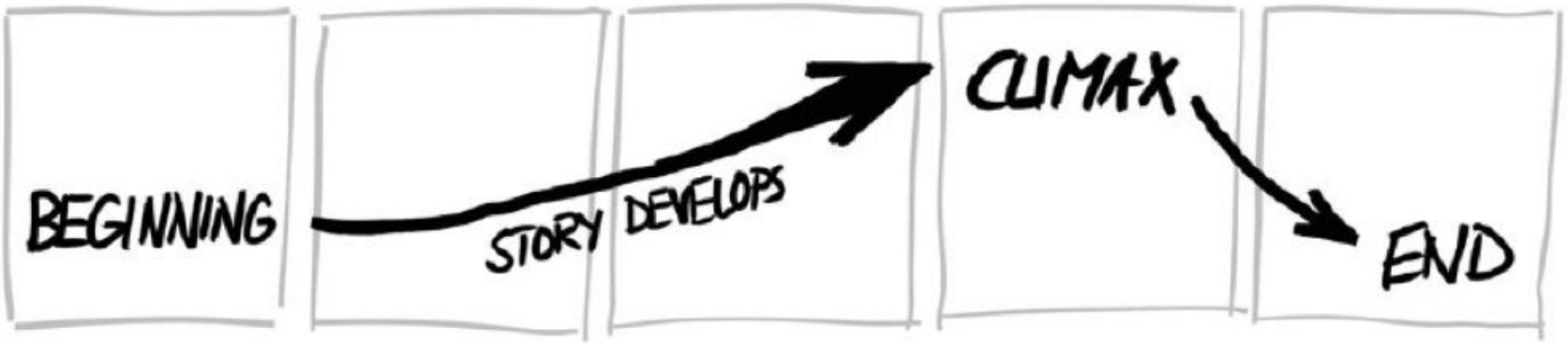
Story Creation



ACTIVITY 1: Audience (10min)

ACTIVITY 2: Messages (15min)

Story structure: **Drama**



Story Structure

Story Structure

Introduction
Context
Problems
...

Curiosity

Audience reaction

Story Structure

Introduction
Context
Problems
...

Events, facts,
Relations, surprise,
Findings, insight
...

Curiosity

Understanding

Audience reaction

Story Structure

Introduction
Context
Problems
...

Curiosity

Events, facts,
Relations, surprise,
Findings, insight
...

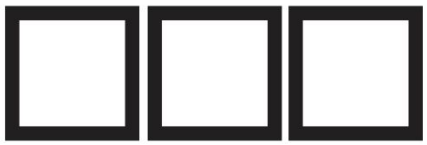
Understanding

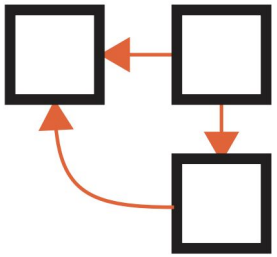
Conclusion,
Resolution,
Take-home
Call-to-action,
...

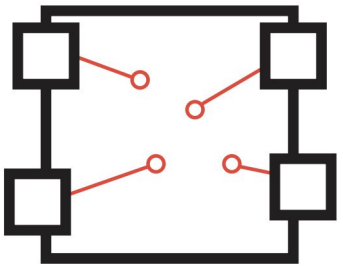
Action

Audience reaction

Narrative Structures

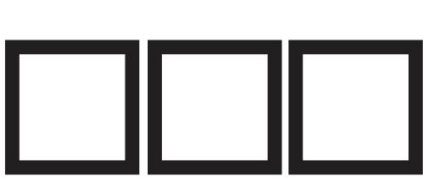


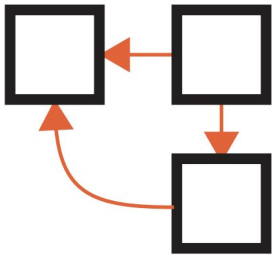


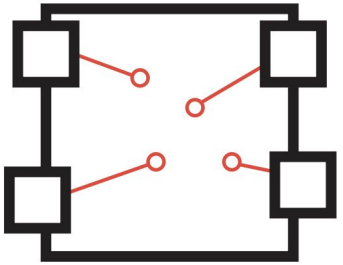


Author driven ⟷ **Reader driven**

Narrative Structures



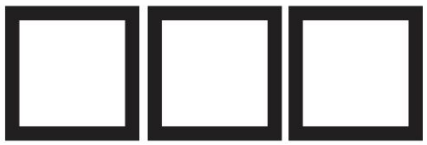


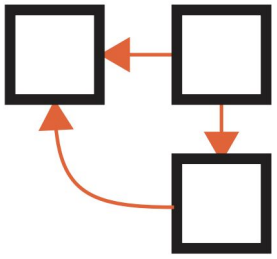


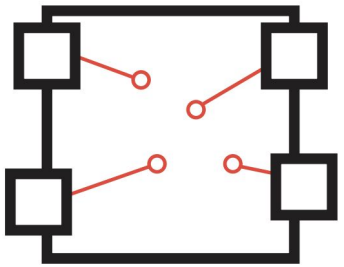
Author driven ⟷ **Reader driven**

Heavy messaging — No messaging

Narrative Structures





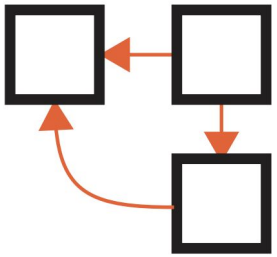


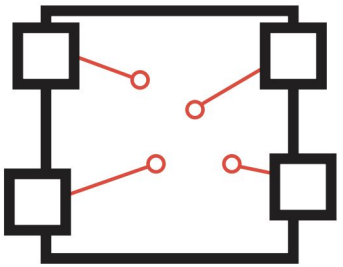
Author driven ⟷ **Reader driven**

Heavy messaging — No messaging

No interactivity — Free interactivity

Narrative Structures





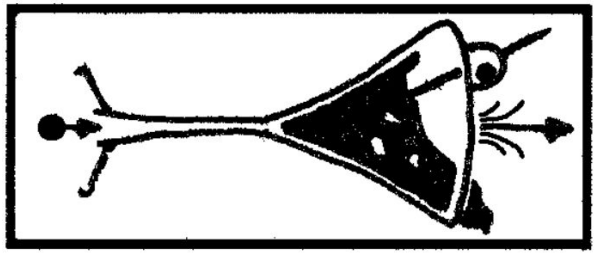
Author driven ⟷ **Reader driven**

Heavy messaging — No messaging

No interactivity — Free interactivity

Linear — Interactive

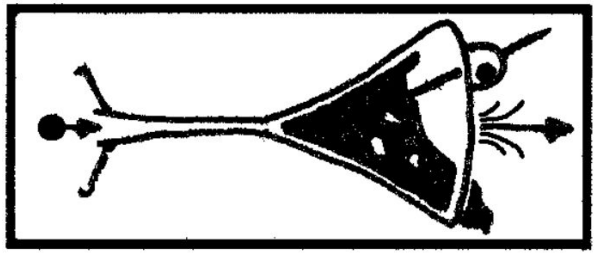
Narrative Structures



Martini-glass Structure
Guidance first, then exploration

Segel E, Heer J. Narrative visualization: Telling stories with data. IEEE transactions on visualization and computer graphics. 2010 Oct 28;16(6):1139-48.

Narrative Structures



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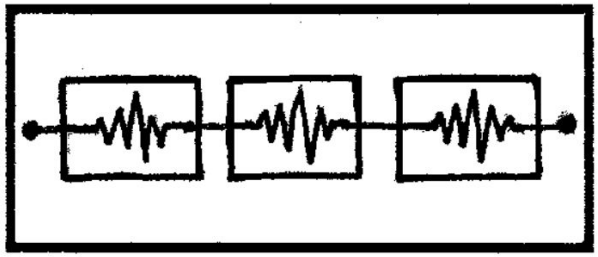

Interactive slideshow
Overall structure
+ local exploration

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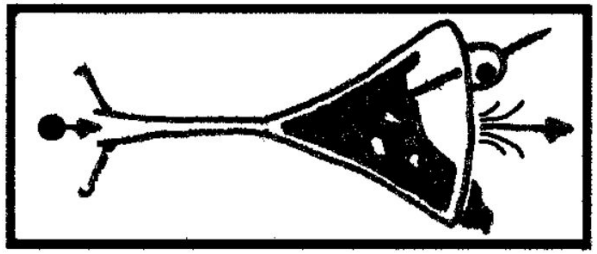
Narrative Structures



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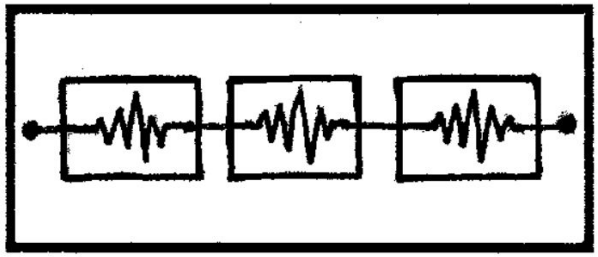

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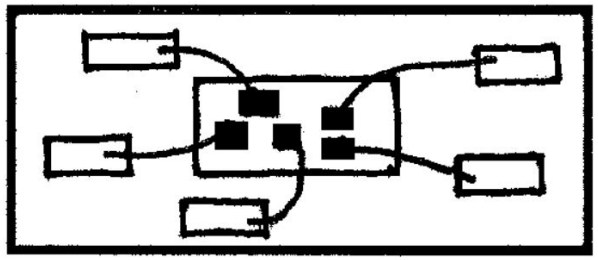
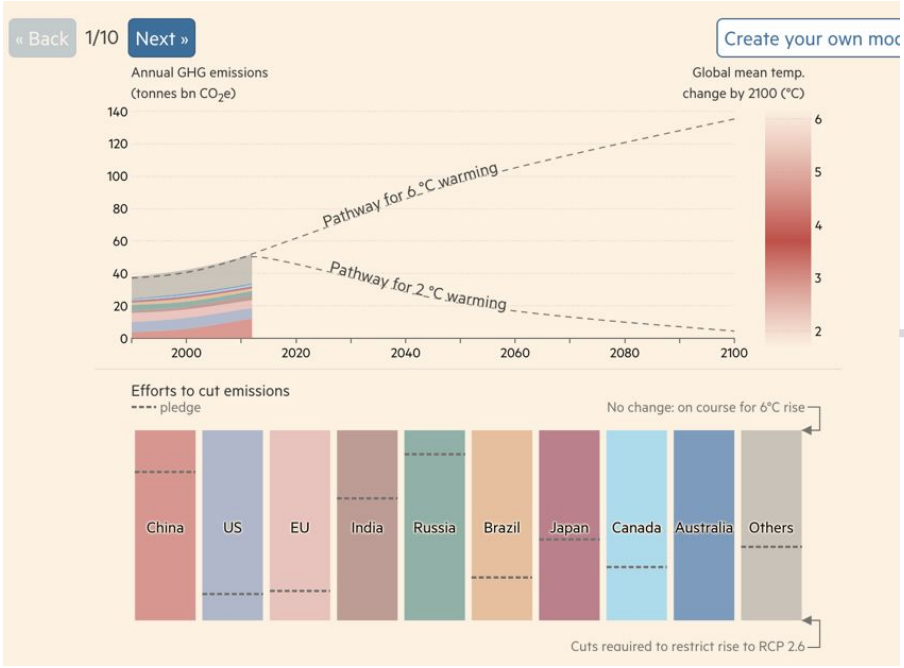
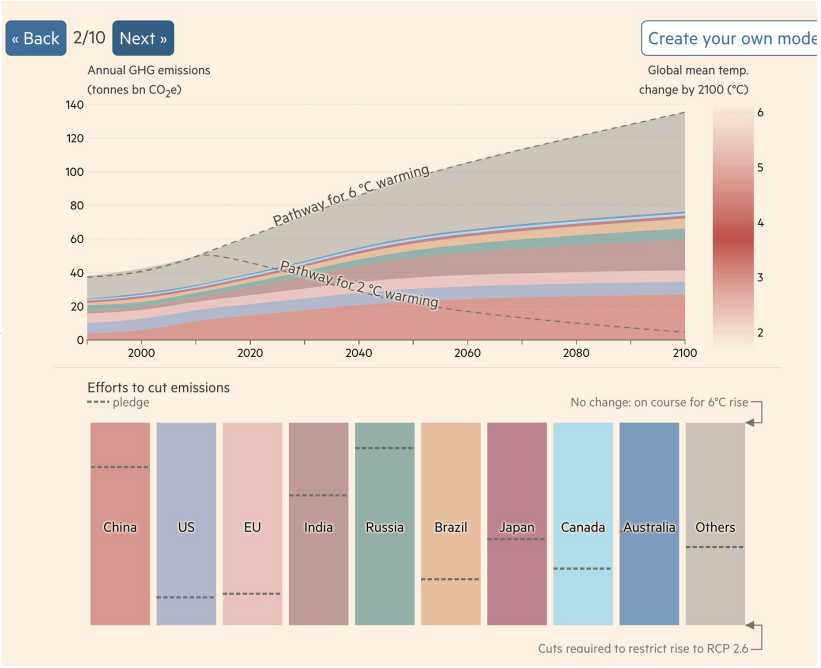


Drill-down story
Largely reader driven

Segel E, Heer J. Narrative visualization: Telling stories with data. IEEE transactions on visualization and computer graphics. 2010 Oct 28;16(6):1139-48.

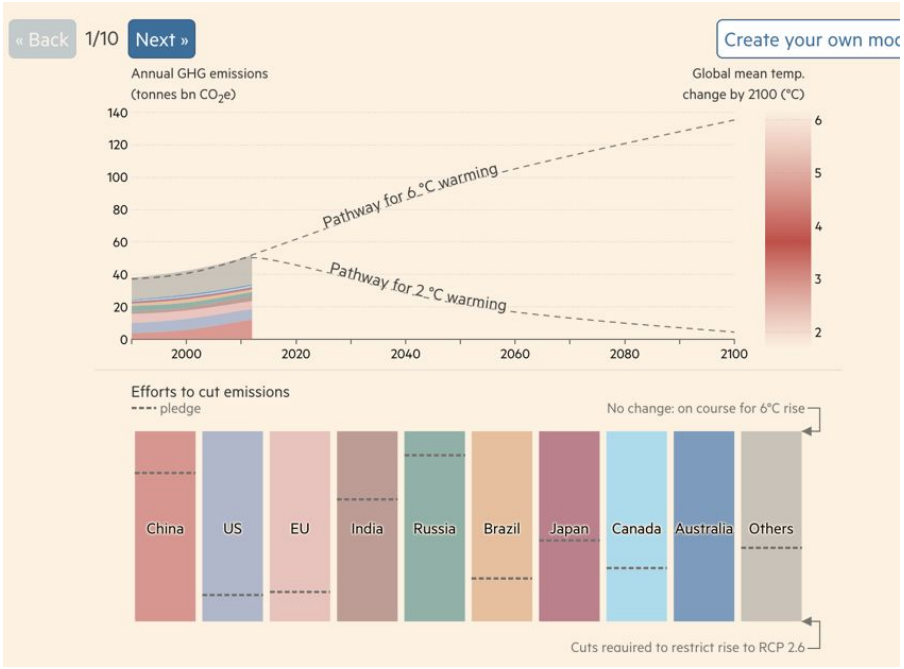
Narrative structures:
Interactive Slideshow

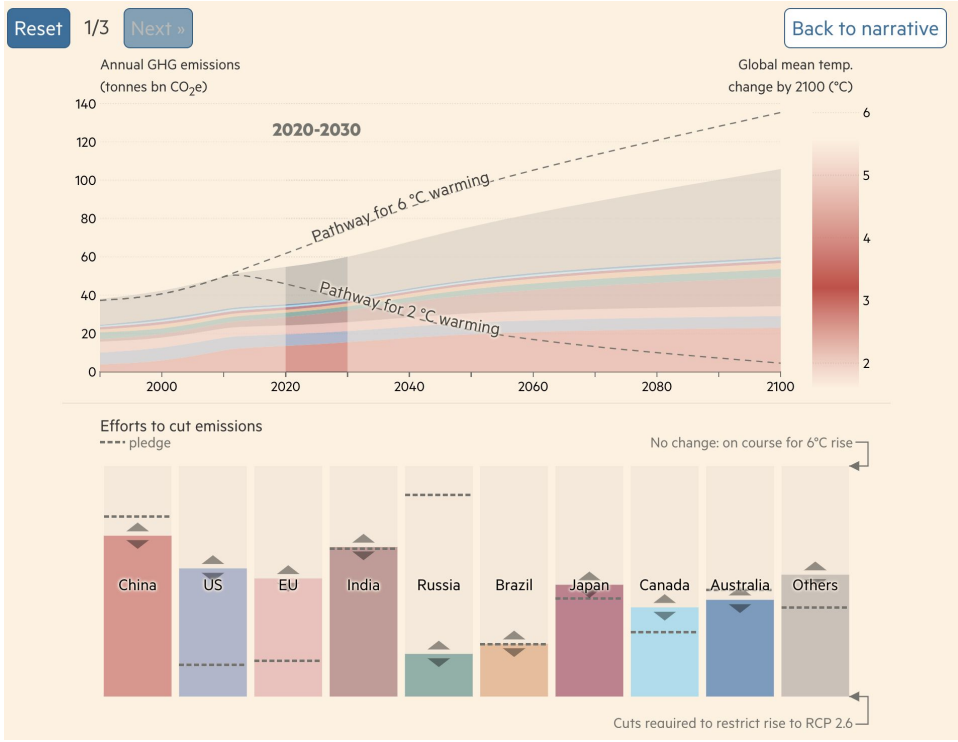




https://ig.ft.com/sites/climate-change-calculator/

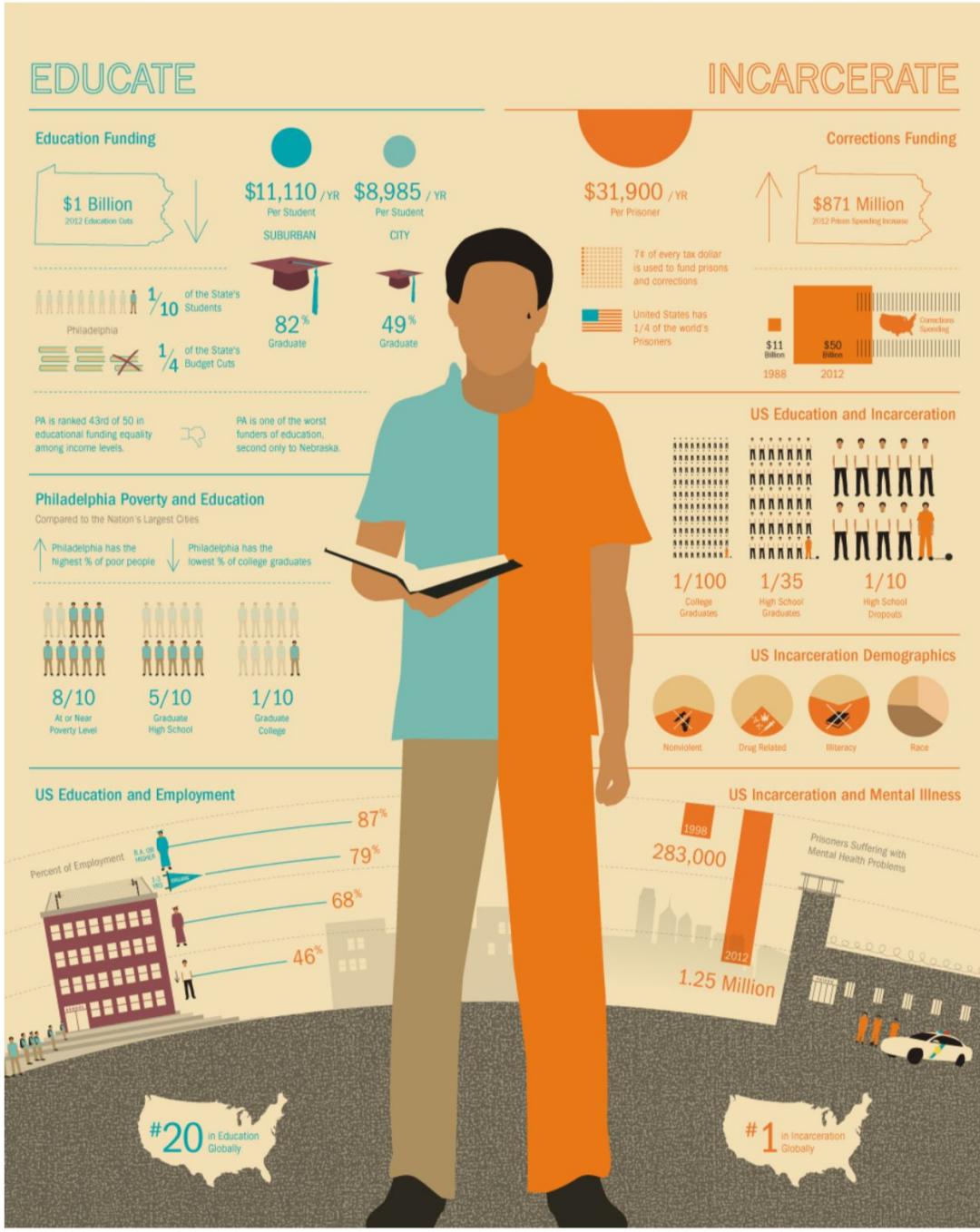
Narrative structures:
Martini-glass Structure





https://ig.ft.com/sites/climate-change-calculator/

Narrative structures: **Drill-down story**



ACTIVITY 3: Scripting (25min)

Individually: 10min

Group: 15min

BREAK

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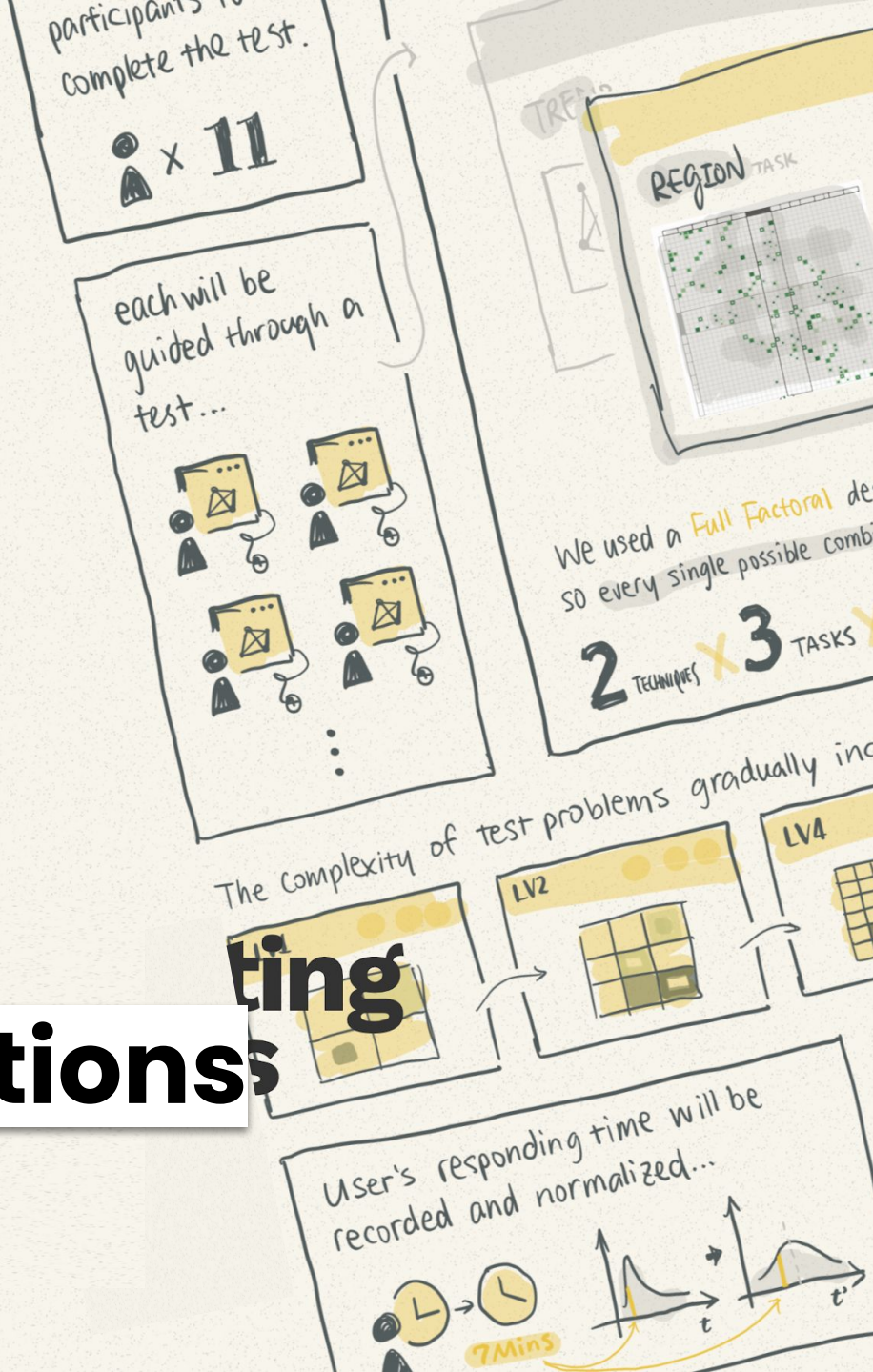
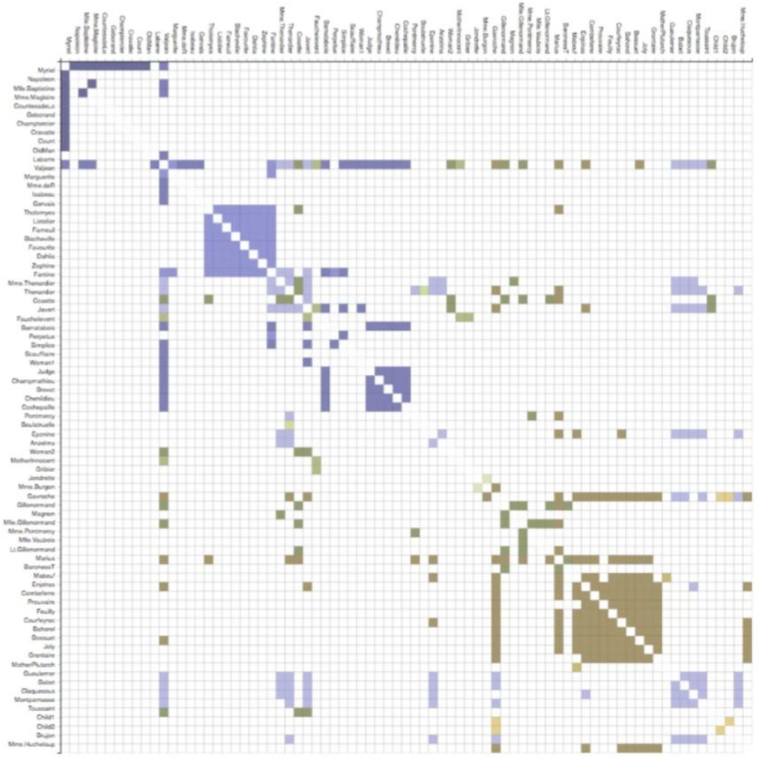
Activity II

Choose Visualizations

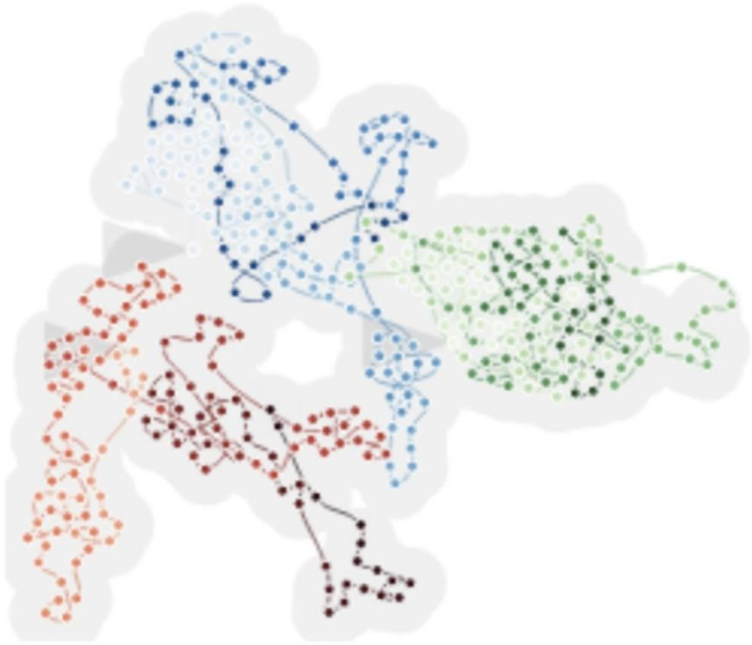


Do you know these visualizations?



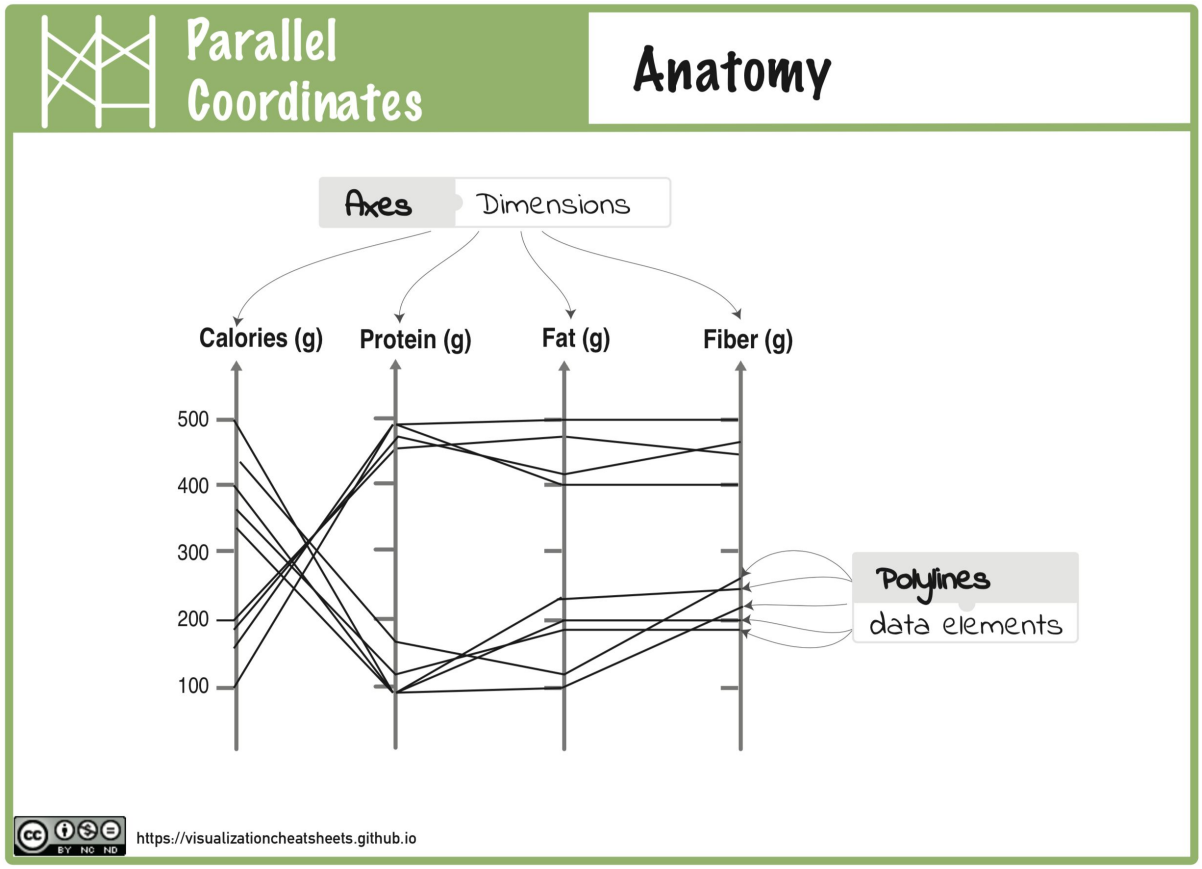
Les Misèrables co-occurrence network

https://github.com/micahstubbs/d3-adjacency-matrix-layout



Bach, B., Shi, C., Heulot, N., Madhyastha, T., Grabowski, T., & Dragicevic, P. (2015). Time curves: Folding time to visualize patterns of temporal evolution in data. IEEE transactions on visualization and computer graphics, 22(1), 559-568.

Visualization Cheat Sheets

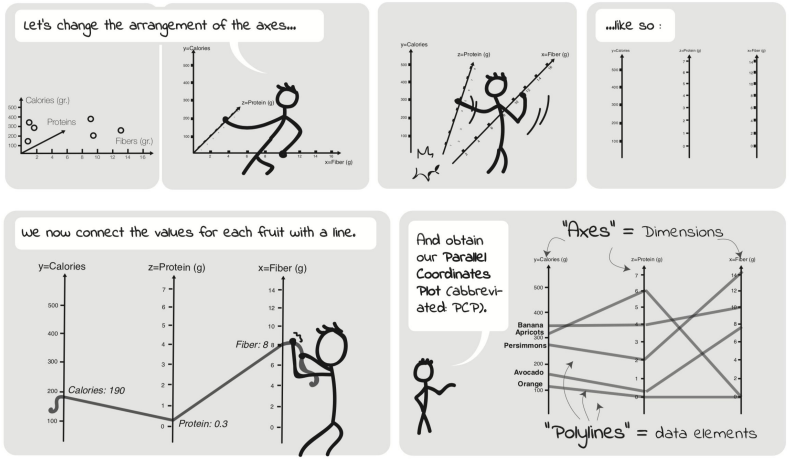


Wang, Z., Sundin, L., Murray-Rust, D. and Bach, B., 2020, April. Cheat Sheets for Data Visualization Techniques. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-13).

https://visualizationcheatsheets.github.io/

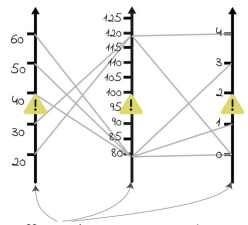
Visualization Cheat Sheets

Parallel Coordinates — Construction



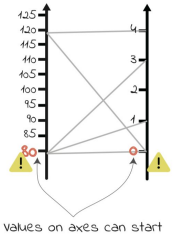
Parallel Coordinates — Pitfalls

Axis scales



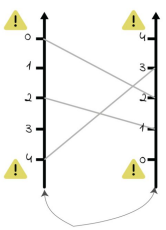
Different dimensions usually have different scales and units.

Truncated axes



Values on axes can start form values other than '0'.

Axes order



Values on axes can be either decending or acending.

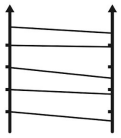
Parallel Coordinates — Visual Patterns

Parallel lines

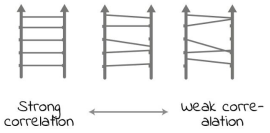
Positive Correlation

Correllations indicate that high values in on data dimensions co-occur with high values in another dimension.

Correllations are not causations!



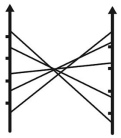
A correlation is visible through rather parallel polylines between two axes.



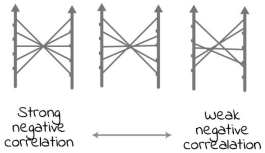
Crossing lines

Negative Correlation

Inverse correlations indicate that high values in one data dimension co-occur with low values in another data dimension.



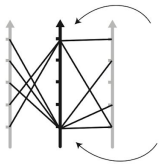
An inverse correlation is visible through lots of crossing polylines between two axes.



Converging lines

Groups

Groups indicate many elements with the same value or similar values.

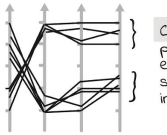


Groups are visible by many lines intersecting an axis at the same position.

Grouped lines

Clusters

Clusters indicate data elements with similar values across several dimensions.



Clusters are visible as polylines 'following' each other across several axes, resulting in bundles.

Wang, Z., Sundin, L., Murray-Rust, D. and Bach, B., 2020, April. Cheat Sheets for Data Visualization Techniques. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-13).

ACTIVITY 4: Visualization

https://visualizationcheatsheets.github.io/

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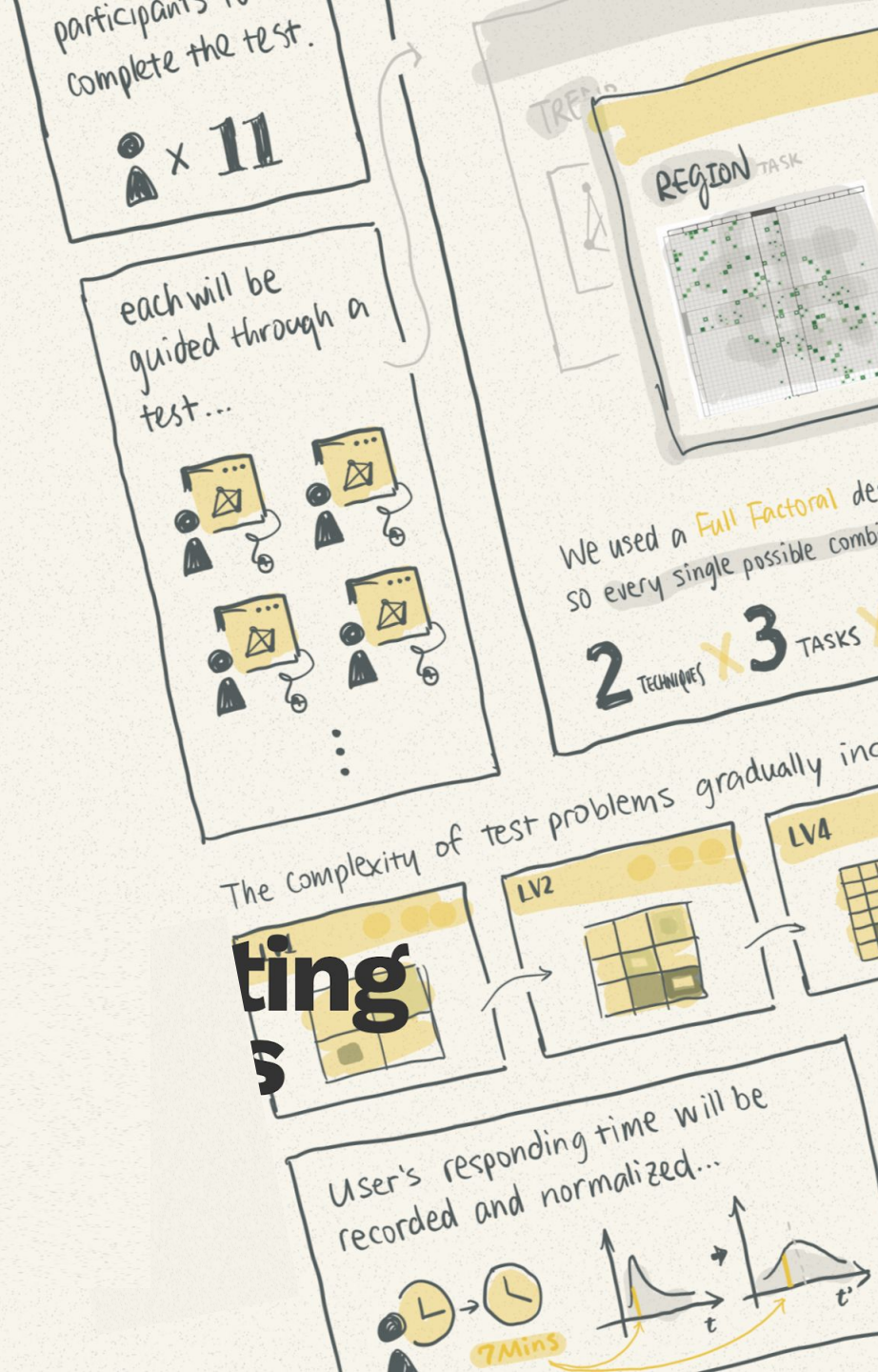
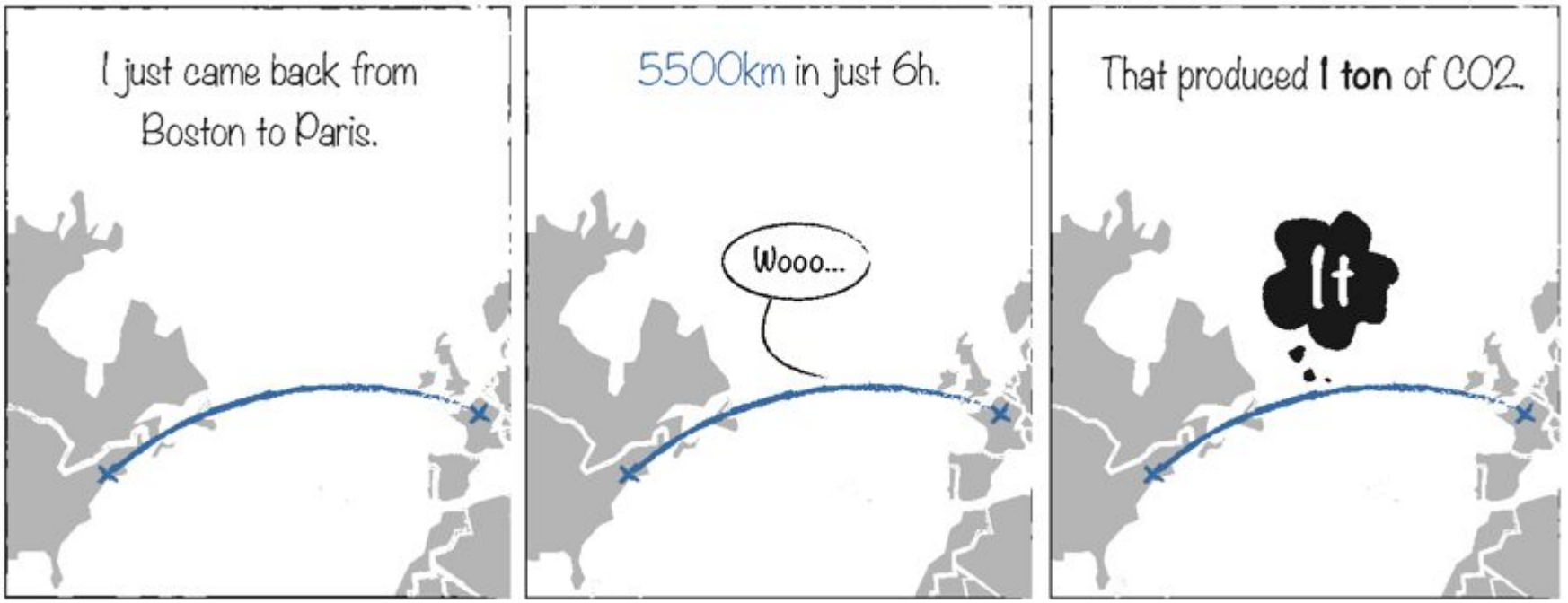
Activity III
Storyboarding



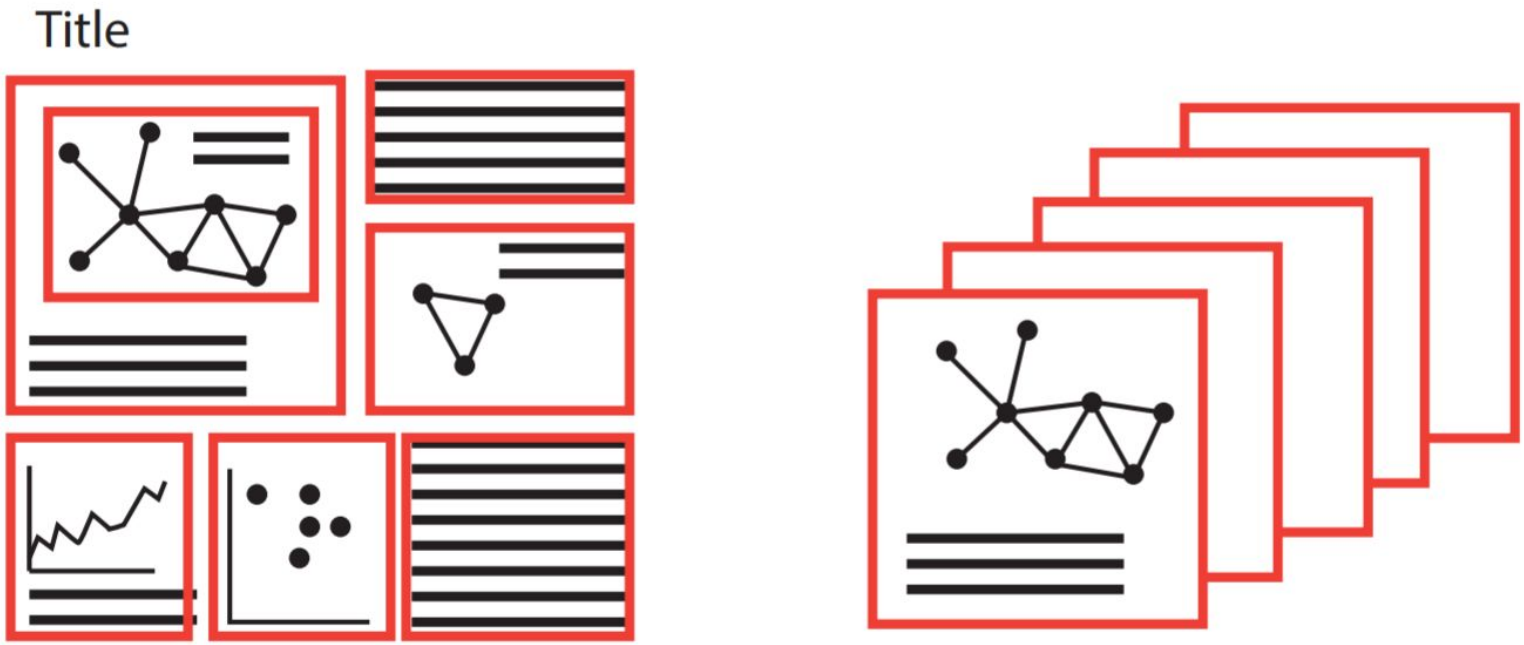
Panel

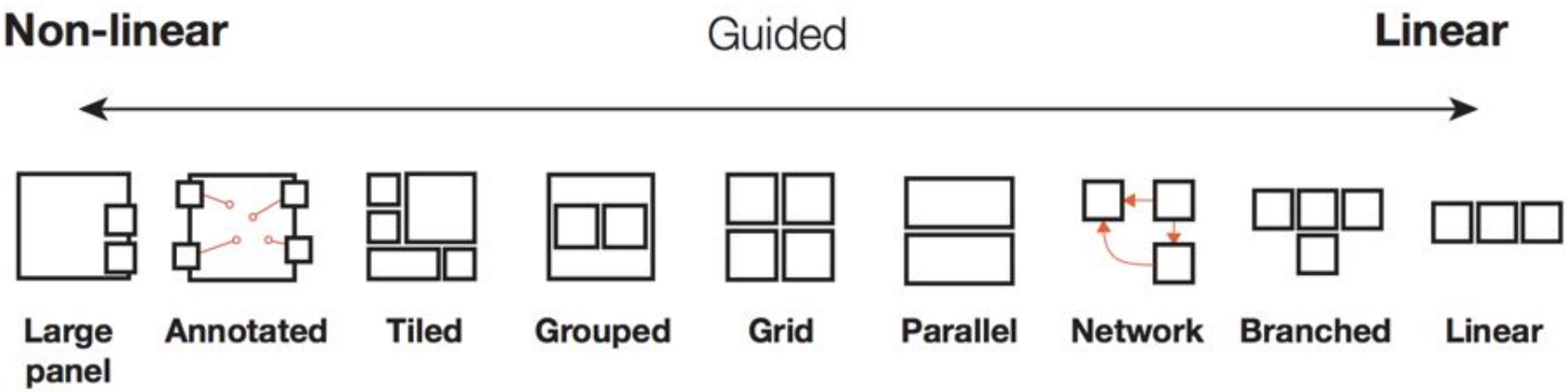
Panel



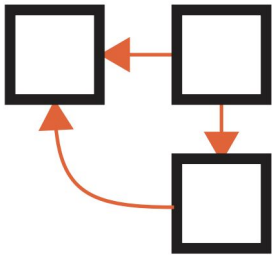
Sequence

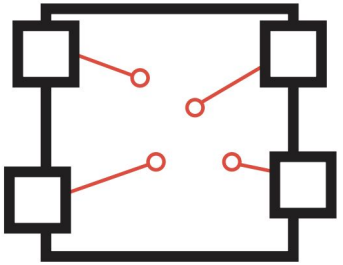
Panels




Non-linear
Guided
Linear
Large panel
Annotated
Tiled
Grouped
Grid
Parallel
Network
Branched
Linear

Narrative Structures





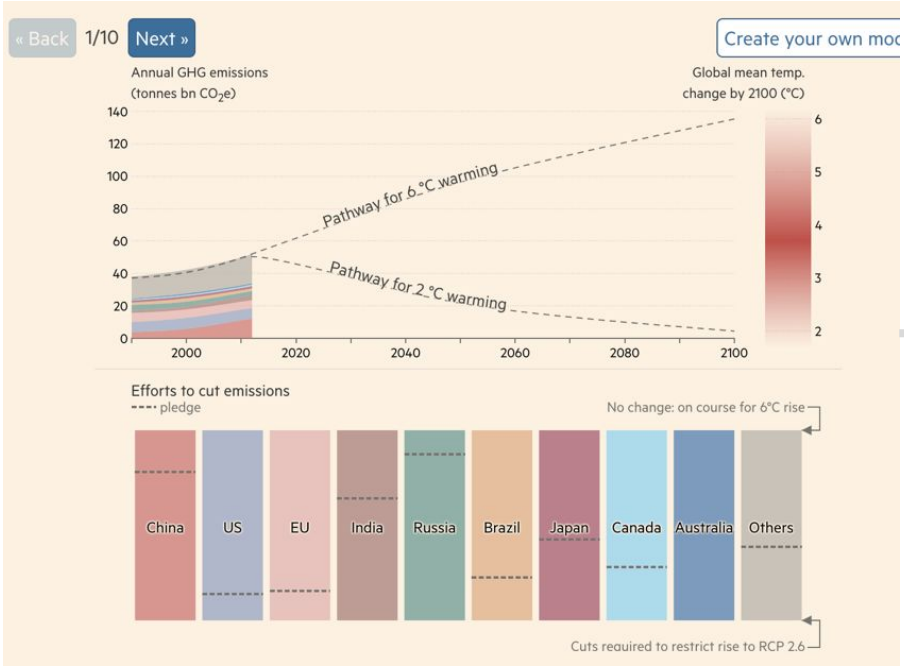
Linearity ⟷ Interactivity

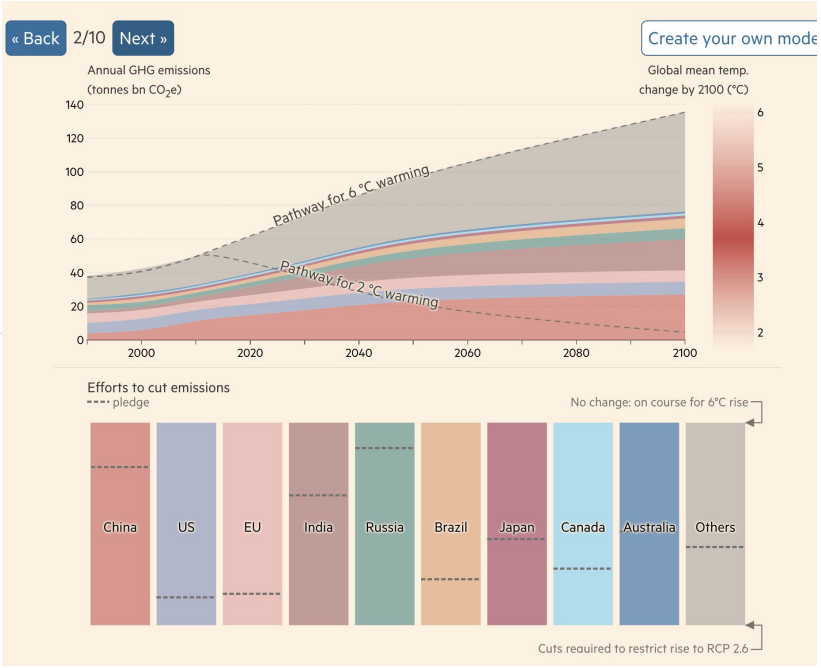
Author driven **Reader driven**

Heavy messaging No messaging

No interactivity Free interactivity

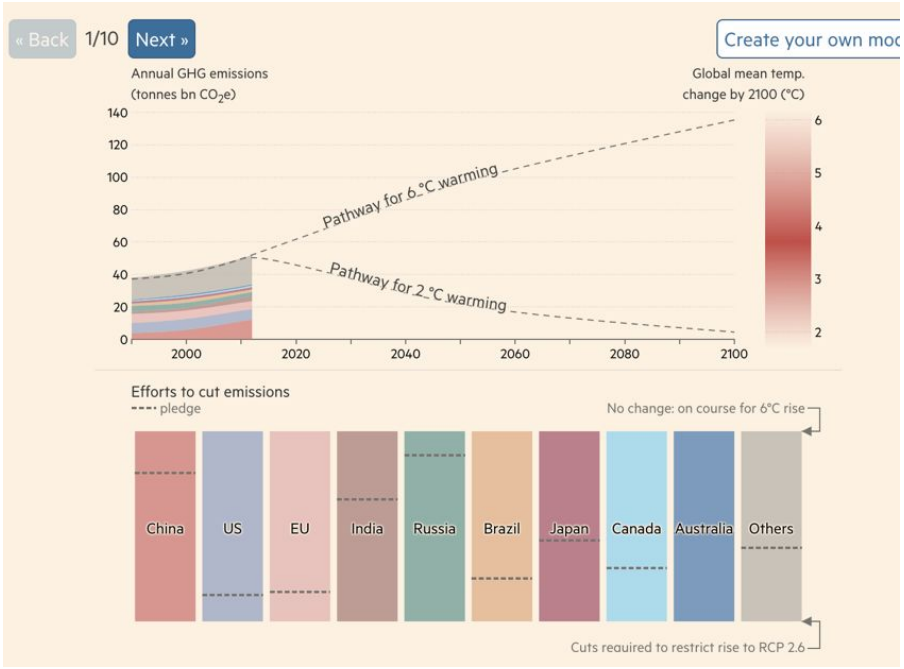
Narrative structures:
Interactive Slideshow

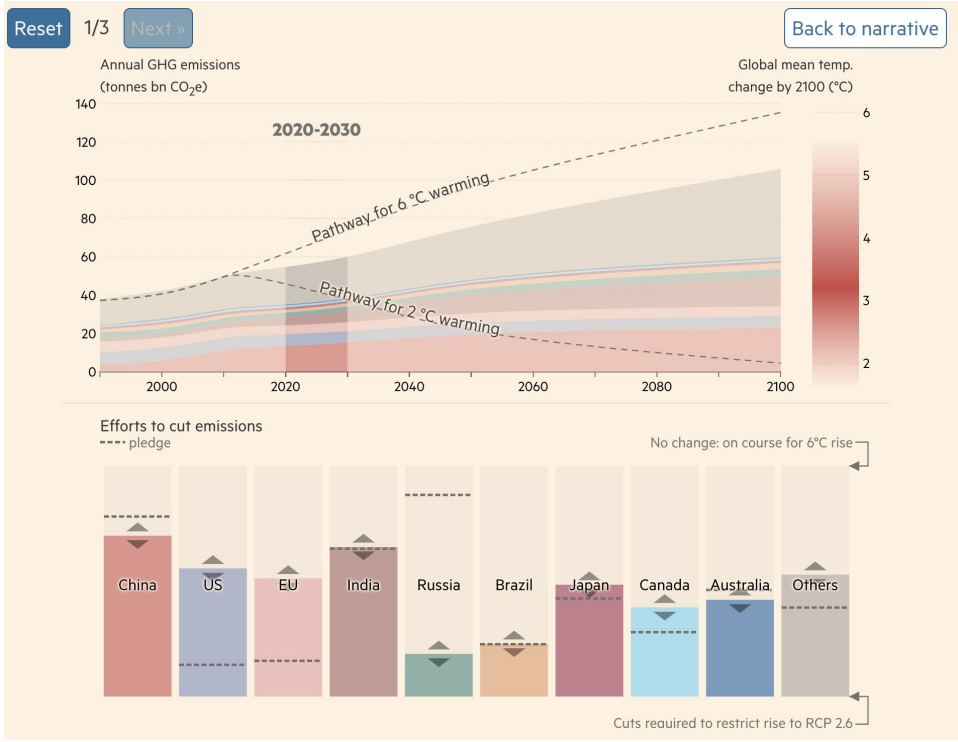




https://ig.ft.com/sites/climate-change-calculator/

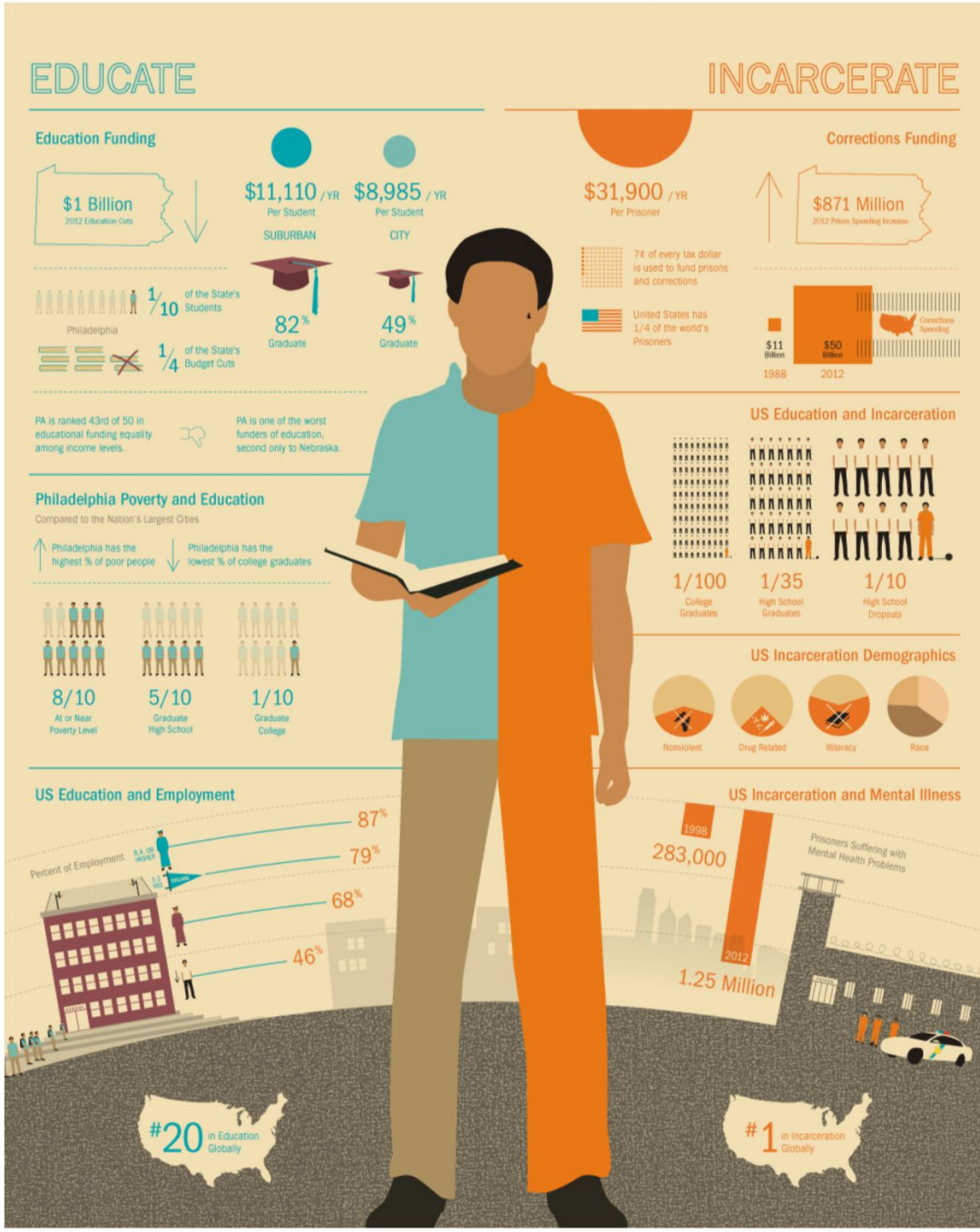
Narrative structures:
Martini-glass Structure





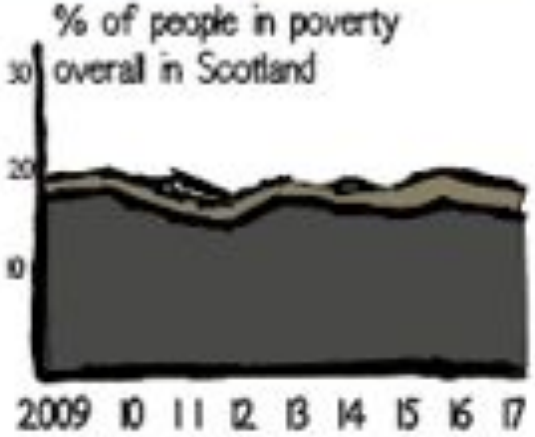
https://ig.ft.com/sites/climate-change-calculator/

Narrative structures: **Drill-down story**

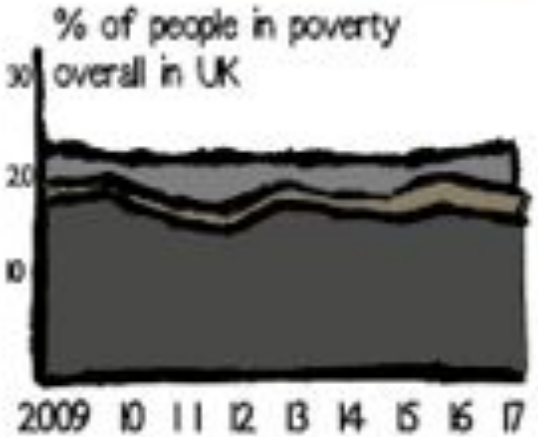


Build-up

For the last decade, this poverty rate has remained virtually unchanged, hovering around 16%.



This is only slightly better than the poverty rate in Scotland overall, which in 2017 reached 19%.



... which itself is lower than the overall UK rate at around 22%.

Zoom

down from 127 in 2010

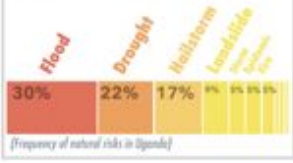
Exposé

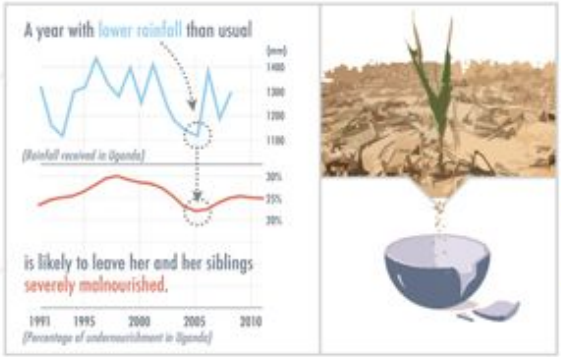
Let's consider a 14 years old girl in Uganda...

She lives in a rural area,

in a situation of poverty, largely dependent on subsistence agriculture

and extremely vulnerable to environmental shocks and stresses:

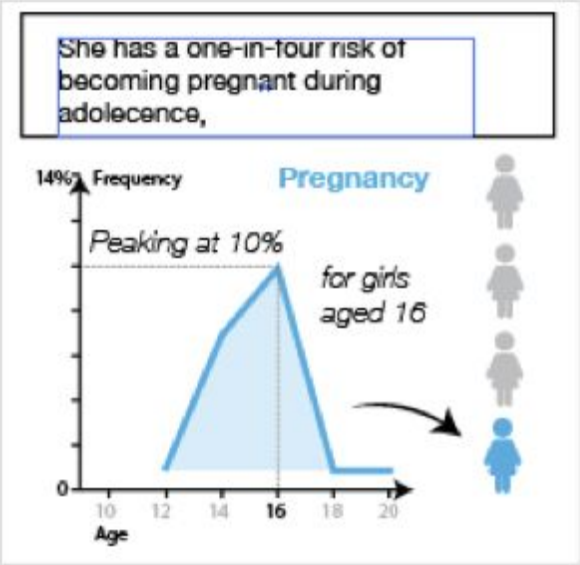


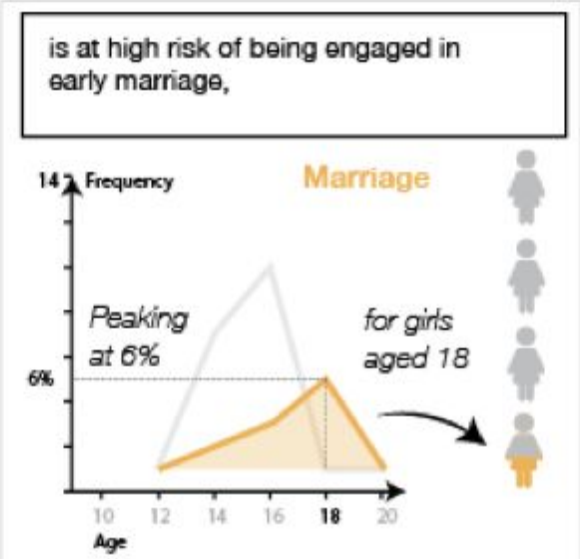


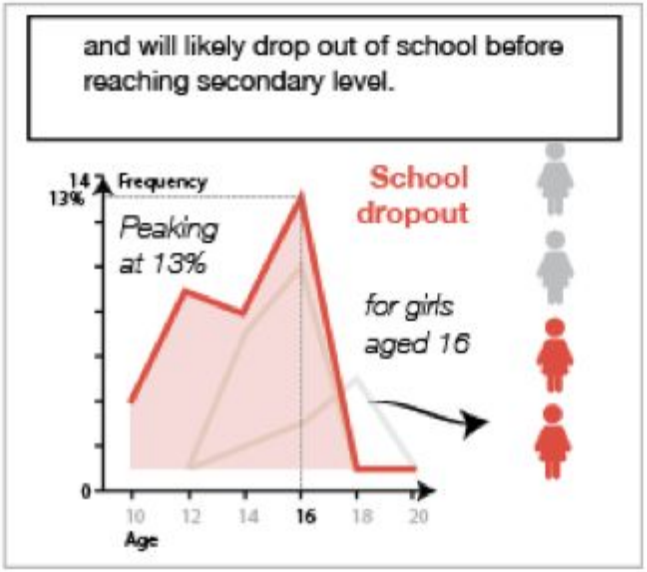
However, if her family is supported to diversify their assets by planting a wider variety of crops,

they are better able to spread their risks and therefore more resilient.

Multiple explanations

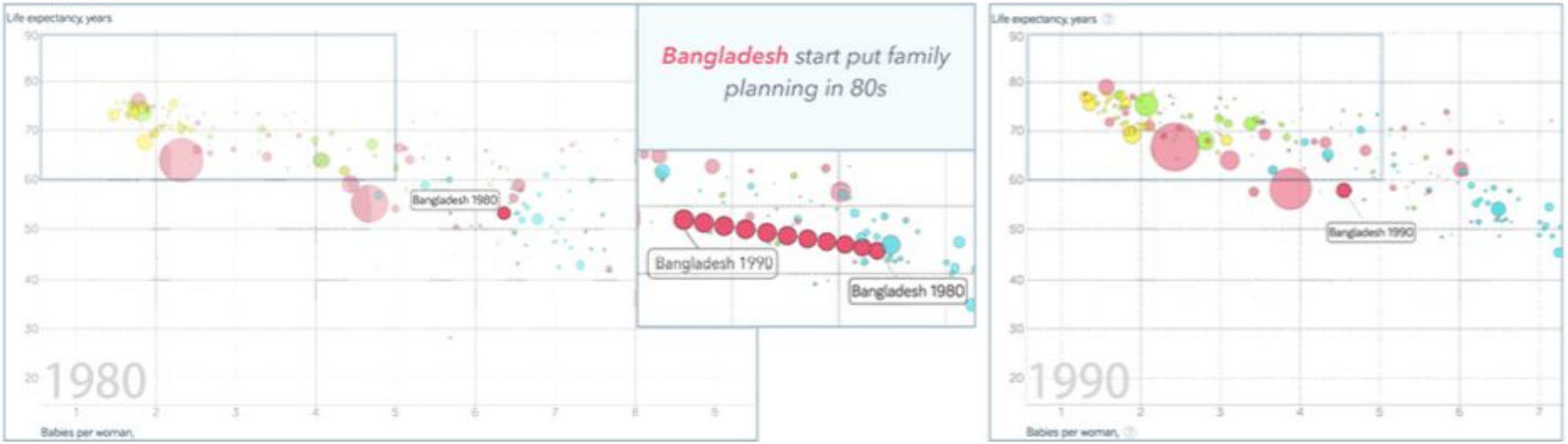




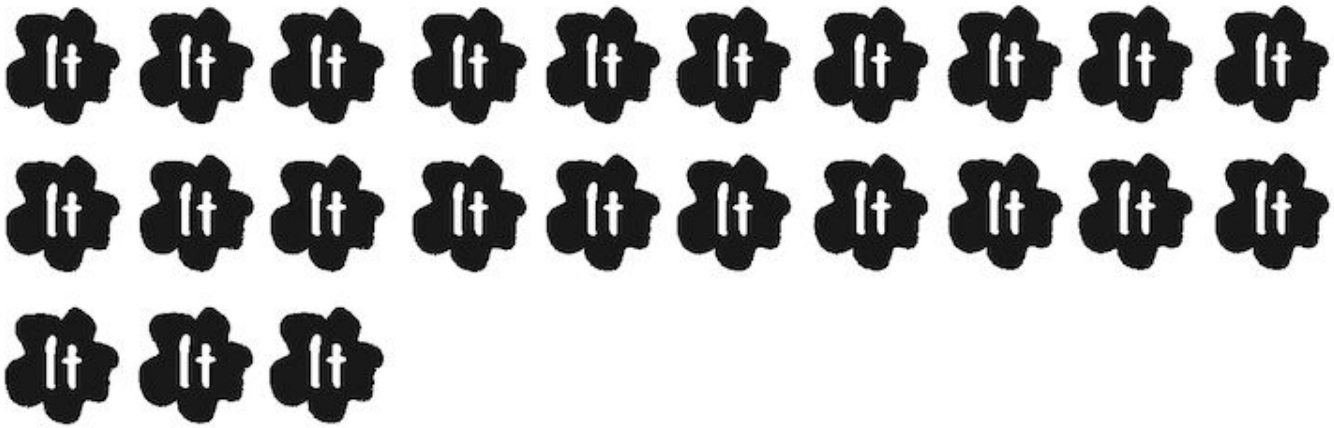


Transitions

Now let's look at the next decadea from 1980 - 1990

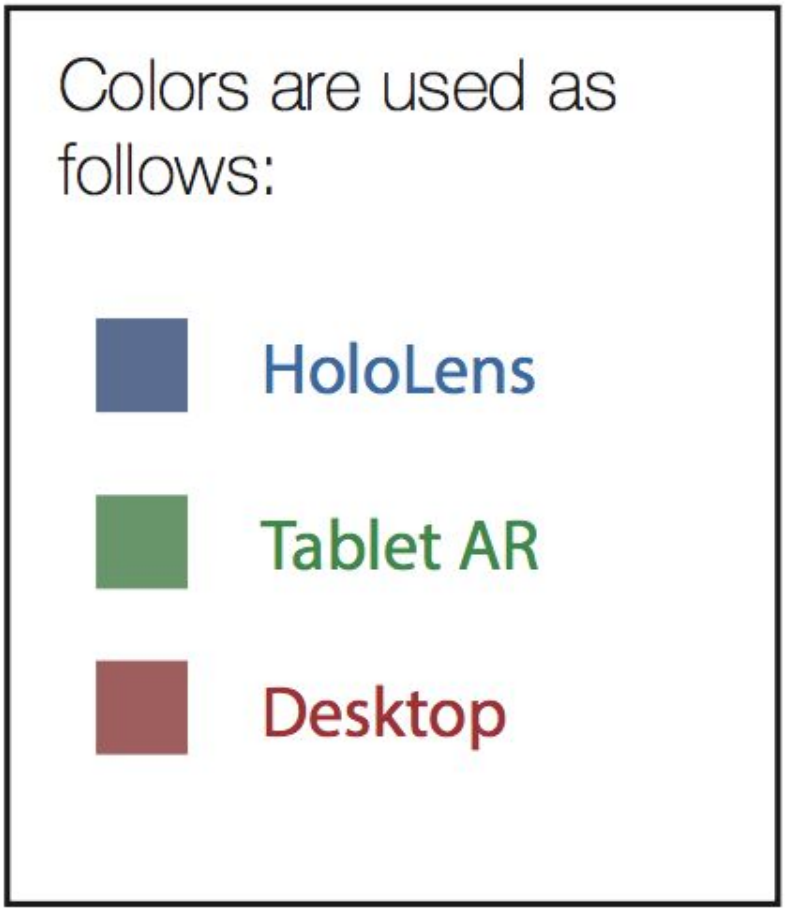


Concretization



23 tons of CO2.

Legend



ACTIVITY 5: Storyboarding

https://datacomics.github.io

https://datacomics.github.io/designpatterns.html

https://statscomics.github.io

THE UNIVERSITY of EDINBURGH

Data-Driven Storytelling with Data Comics

Benjamin Bach,
Zezhong Wang
University of Edinburgh

https://datacomics.github.io/designpatterns.html

VIS HUB University of Edinburgh
Visual+ Interactive Data