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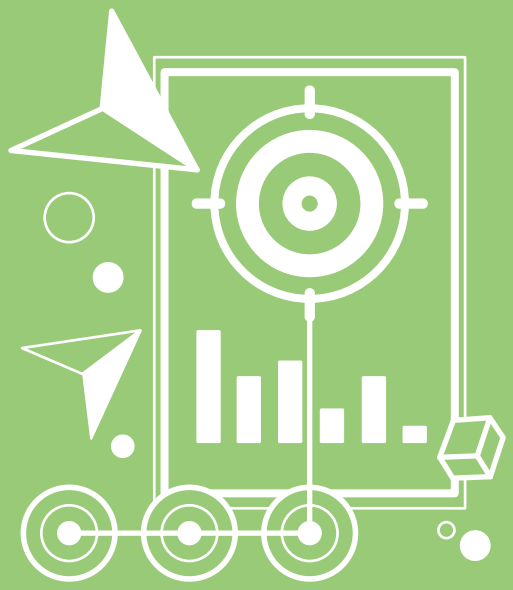
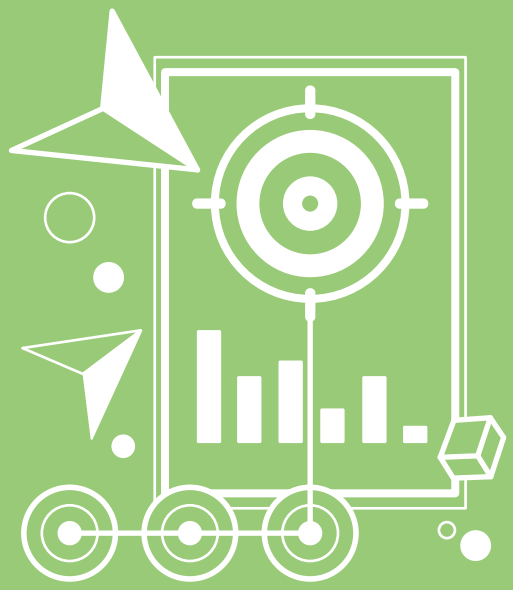


Goal



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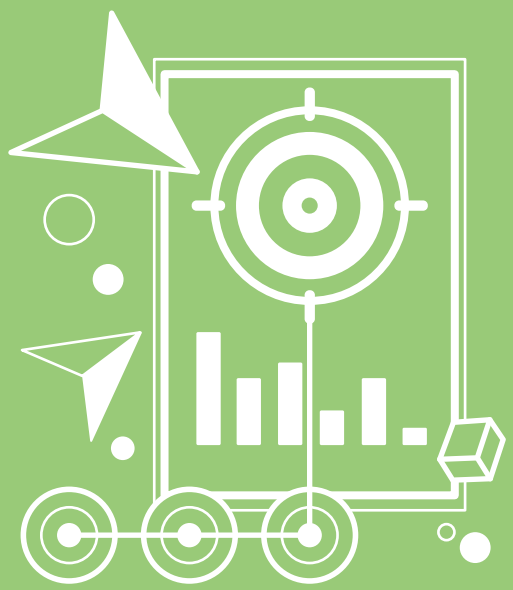

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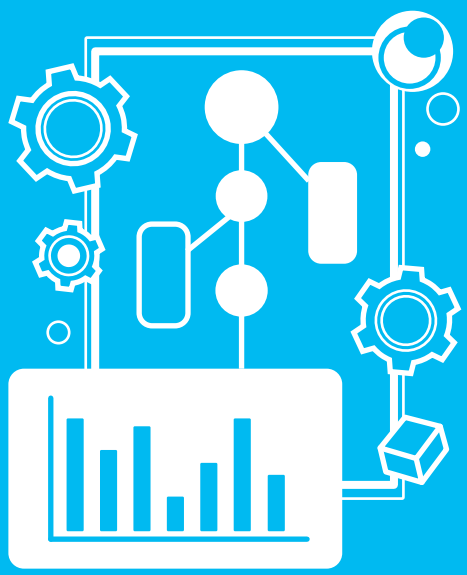

AI-VIS Task

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Goal

Visualization Generation

Categories of Generation Approaches:

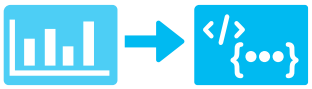
- Turn raw data (like from a spreadsheet) into charts or graphs.
- Like solving a puzzle, each insight from one visualization helps decide the next one to explore.
- Use a ready-made chart design and fill it with your data, like matching a picture to a frame.
- Create visuals that tell a story with context, not just show numbers.

Goal

Visualization Enhancement

- Retargeting: Change visuals so they work well on different screens or devices.
- Summarizing: Add easy-to-read captions or notes to explain the visuals.
- Question-Answering: Let the system answer questions about what the visual shows.
- Interactivity: Make visuals interactive so users can explore and understand them better.

AI-VIS Task



Transformation

What It Does: Converting visualization images into code.

Why It's Important: Enables improving and analyzing visualizations.

The Challenge: Hard to capture both the visual encoding and the underlying data, especially for non-standard charts.

Goal

Visualization Analysis

- Retrieval: Search for charts or graphs that match what you're looking for, like using a search engine for visualizations.
- Mining: Look through lots of visualizations to find patterns or useful insights.
- Visual Data Analysis: Analyzing data from charts.

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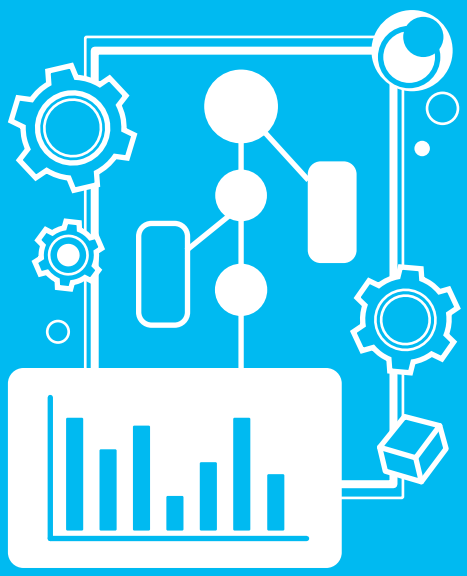

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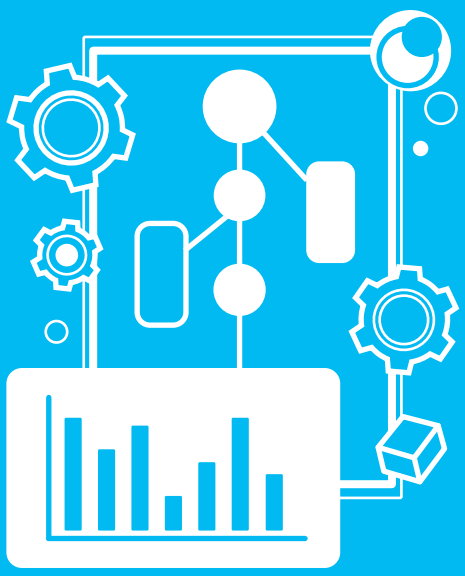

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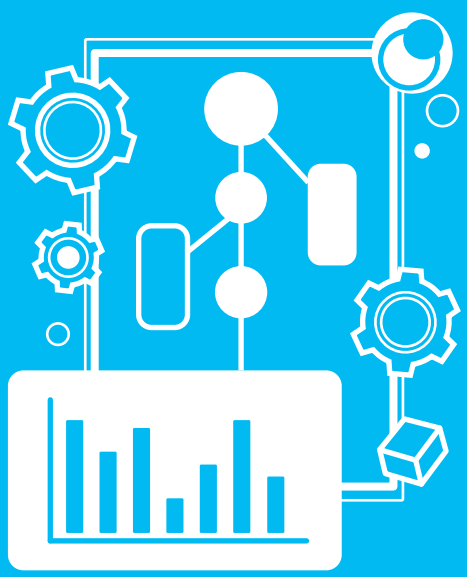

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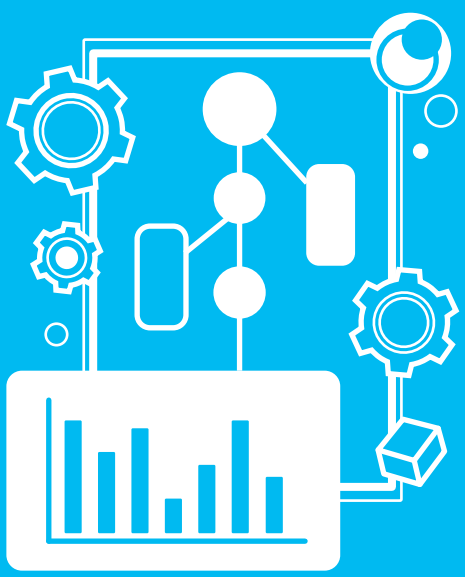

AI-VIS Task

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AI-VIS Task

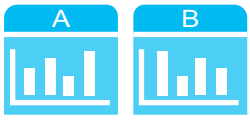
Assessment

What It Does: Measures how clear, accurate, or user-friendly a chart is.

Why Important: Helps improve design and suggest better visualizations.

Challenge: Hard to evaluate since “good” can be subjective.

AI-VIS Task



Comparison

What It Does: Measures how similar or different two charts are.

Why Important: Helps create and analyze visualizations by identifying key differences.

Challenge: Depends on manual feature selection and formulas, often missing what users actually want or need.

AI-VIS Task

Querying

What It Does: Finds specific visualizations based on user needs, like keywords, labels, or similar examples.

Why Important: Makes it easier to find and analyze the right visualizations quickly.

Challenge: Many methods work only for certain chart types, and it’s hard to fully understand and match what users are looking for.

AI-VIS Task

Reasoning

What It Does: AI analyzes visualizations and provide insights or summaries.

Why Important: Helps users understand visualizations by offering explanations or answers.

Challenge: It’s difficult to interpret visualizations accurately and answer questions about them.

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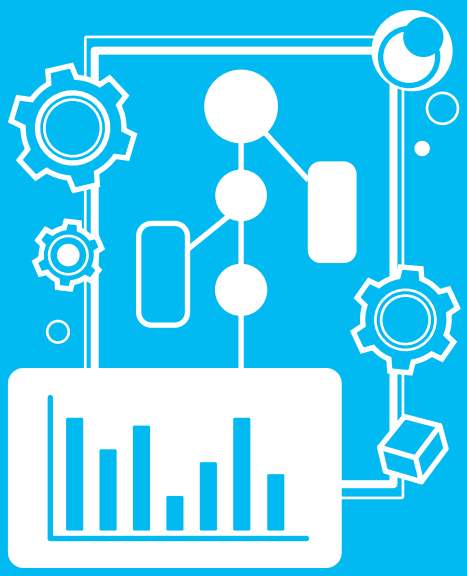

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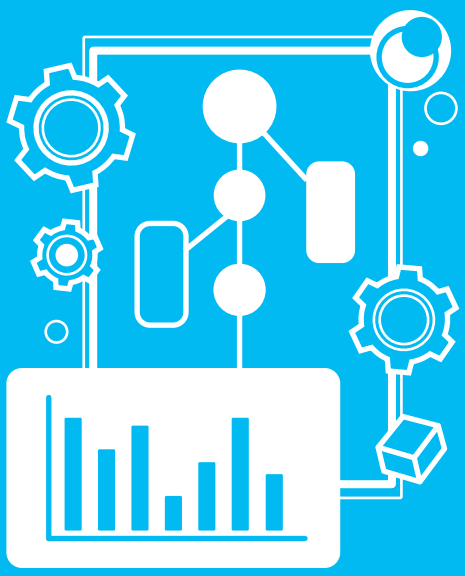

AI-VIS Task

Technology

Technology

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AI-VIS Task

Recommendation

What It Does: Suggests the best chart type or design to represent data, like recommending a line chart for sales trends.

Why Important: Helps automate and simplify the process of creating effective visualizations.

Challenge: It's hard to define the right metrics and decide which insights are the most important to highlight.

AI-VIS Task

Mining

What It Does: Finds insights and patterns by analyzing large collections of visualizations.

Why Important: Helps uncover common themes and design principles to improve visualization practices.

Challenge: Patterns found might not lead to useful insights without proper interpretation.

Technology

Mobile and Web Applications

For example: personal health, services.

Improve daily life with health tracking and task management, but raise ethical concerns about privacy, data security, and how openly AI and visualizations show what data they collect, how they use it, and who can access it.

Technology

Social Networks and Forums

For example: crowd-sourcing, social media.

Connect people globally for collaboration and idea-sharing but also risk spreading misinformation, deepfakes, and misleading visuals, undermining trust and public opinion.

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Technology

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Technology

Public Installations and Displays

For example: ambient displays, data murals, data sculptures, installations.

Make data engaging through interactive, immersive experiences, but also raise ethical concerns about collecting people's data without them knowing, which calls for transparency and respect for privacy.

[1] d'Ignazio, Catherine, and Lauren F. Klein. "Feminist data visualization." Workshop on Visualization for the Digital Humanities (VIS4DH), Baltimore. IEEE., 2016.
[2] Waern, Annika. "The ethics of unaware participation in public interventions." *proceedings of the 2016 CHI conference on human factors in computing systems*. 2016.

Technology

Internet of Things (IoT)

For example: smart spaces, smart TVs, educational tools, in general.

Enhances convenience with smart devices and systems but poses ethical risks like privacy invasion and loss of autonomy, requiring strict standards for transparency and consent.

Technology

Wearables and Biosensors

For example: biosensing, fashion technologies, body integration.

Transform health monitoring with real-time insights, but ethical concerns about data control and privacy highlight the need for user autonomy in visualization and sharing.

Curmi, Franco, Maria Angela Ferrario, and Jon Whittle. "Sharing real-time biometric data across social networks: Requirements for research experiments." *Proceedings of the 2014 conference on Designing interactive systems*. 2014.

Technology

Games

For example: playful narratives, virtual reality, for leisure, with cultural references, multiplayer.

Ensuring cultural elements are represented authentically and avoiding appropriation and biases, preserving the integrity and inclusivity of gaming worlds.

Vasalou, Asimina, et al. "Problematizing cultural appropriation." *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play*. 2014.

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Technology

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Technology

Broadcast Media

For example: video streaming platforms, documentaries, news media.

Data visualization can help explain complex issues, but as automation grows, ensure that it does not misrepresent, marginalize, or favor certain groups over others in visualizations. Avoid manipulative or misleading visuals that could distort understanding or push a biased agenda.

Correll, Michael. "Ethical dimensions of visualization research." *Proceedings of the 2019 CHI conference on human factors in computing systems*. 2019.

Technology

Data Repositories

For example: historical archives, DNA repositories, learning analytics.

Use visualization to uncover insights, like genetic links to diseases, but raise ethical concerns about privacy and the long-term impact on individuals whose data is stored.

Lin, Jimmy, et al. "We could, but should we? Ethical considerations for providing access to GeoCities and other historical digital collections." *Proceedings of the 2020 Conference on Human Information Interaction and Retrieval*. 2020.

Technology

VR/AR Technologies

VR and AR are transforming tourism, education, gaming, and healthcare with immersive experiences, like virtual field trips or medical training simulations using AI and virtual tools.

Hirve, Sumit A., et al. "An approach towards data visualization based on AR principles." 2017 International Conference on Big Data Analytics and Computational Intelligence (ICBDAC). IEEE, 2017.

Technology

Others

For example: shape-changing interfaces, end-of-life technologies, drones.

By turning data into something visible and tangible, we make communication more intuitive, and by visualizing digital memories, we help people form meaningful emotional connections through data.

[1] Alexander, Jason, et al. "Grand challenges in shape-changing interface research." *Proceedings of the 2018 CHI conference on human factors in computing systems*. 2018.
[2] Massimi, Michael, et al. "Matters of life and death: locating the end of life in lifespan-oriented HCI research." *Proceedings of the sigchi conference on human factors in computing systems*. 2011.

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Principle

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Principle

Transparency

Transparency in AI means clearly explaining how AI systems work, make decisions, and impact users. By using simple, non-technical language and enabling audits, it ensures AI actions can be understood, justified, and trusted.

Principle

Justice and Fairness

Justice in AI focuses on fairness by preventing and addressing bias and discrimination. In visual-ization, this means ensuring unbiased data representation to promote diversity, equality, and fairness in visual outputs.

Principle

Non-Maleficence

Non-maleficence in AI ethics means ensuring systems do not harm individuals or society, prioritizing safety, security, and user well-being while protecting autonomy.

Principle

Responsibility

Responsibility in AI ethics means creators and operators are accountable for their technologies, ensuring ethical development, compliance with laws, and remedies for any issues.

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Principle

Privacy

Privacy in AI ethics is a core value focused on protecting personal data through strong security measures, ensuring AI systems respect user confidentiality and prevent unauthorized access or misuse.

Principle

Beneficence

Beneficence in AI ethics focuses on using AI to enhance well-being, foster societal progress, and create opportunities, ensuring its benefits are widely and fairly shared to support human flourishing.

Principle

Freedom and Autonomy

Freedom and autonomy in AI ethics stress individual choice and self-determination, ensuring people control how AI affects their lives through privacy protections and informed participation.

Principle

Trust

Trust in AI ethics is about creating reliable, secure, and transparent systems, ensuring integrity in development and adherence to ethical design principles.

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Principle

Principle

People-In-Focus

Principle

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Principle

Sustainability

Sustainability in AI ethics prioritizes environmentally friendly development, focusing on energy efficiency, minimizing ecological impact, and creating lasting societal benefits.

Principle

Dignity

Dignity in AI ethics emphasizes respecting human rights and values, ensuring AI enhances dignity by avoiding harm, forced acceptance, and cautious handling of automated decisions and interactions.

Principle

Solidarity

Solidarity in AI ethics promotes shared responsibility to ensure AI benefits are equitably distributed, protecting vulnerable groups, supporting those affected by job changes, and fostering social cohesion through inclusive technology.

People-In-Focus

Age Variations

For example: children, teenagers, and the elderly.

Children may accept some parental monitoring but resist constant surveillance or unexplained data use, which can lead to trust issues. Similarly, ethical practices must avoid exploiting the elderly through manipulative designs that take advantage of their trust or limited technical knowledge.

Kumar, Priya C., et al. "Understanding Research Related to Designing for Children's Privacy and Security: A Document Analysis." *Proceedings of the 22nd Annual ACM Interaction Design and Children Conference.* 2023.

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People-In-Focus

People-In-Focus

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People-In-Focus

Workers with Different Needs

For example: Amazon Mechanical Turk workers, musicians, Uber drivers and home health aides, shipping industry.

Amazon Mechanical Turk workers need fair and engaging interfaces, Uber drivers benefit from clear visualizations of safety and earnings, home health aides require simplified patient data tools, and shipping workers need logistic visuals that prioritize safety and balance.

People-In-Focus

People with Health Conditions

For example: neurological illnesses, mental health diagnosis, substance addiction, cancer.

For individuals with health conditions, tracking technologies often monitor symptoms and behaviors, but negative feedback can worsen mental health or self-esteem. The challenge is to design systems that empower and support patients without causing distress.

People-In-Focus

Marginalized

For example: gender variations, racial variations, various challenges such communication.

We should avoid reinforcing biases or exclusion by ensuring data tools respect and affirm diverse identities. This requires creating inclusive spaces, valuing all voices, and promoting equitable representation to empower marginalized communities.

People-In-Focus

Situational variations

For example: rural, homeless.

For individuals in unique contexts, like rural areas or homelessness, data collection should respect their challenges and socio-cultural backgrounds. Adapting methods, such as participatory workshops, is vital to avoid reinforcing power imbalances and ensure meaningful engagement.

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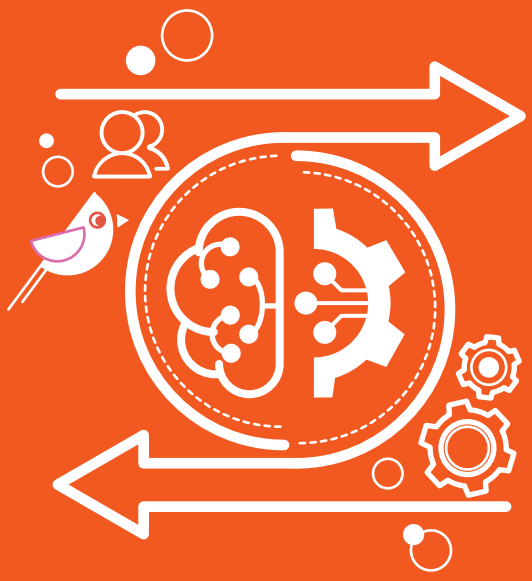
People-In-Focus



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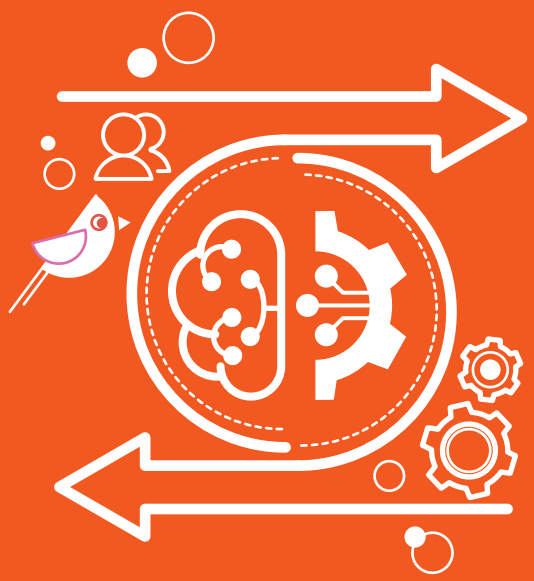

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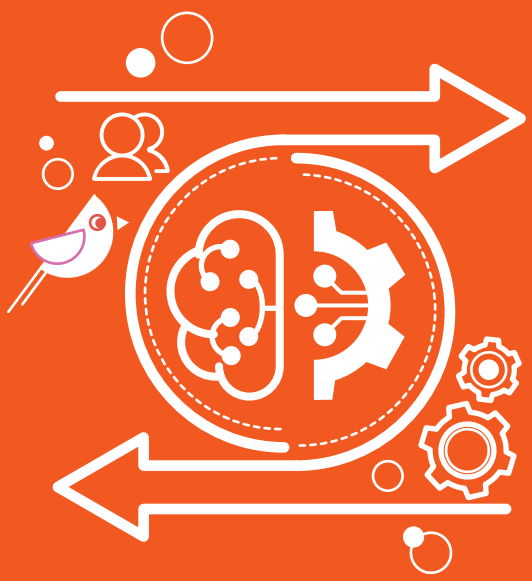

Challenge

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Challenge

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Input Questions:

How much guidance should analytics systems provide to users?

Systems that find insights automatically can help non-experts save time, but they should stay transparent, explain the insights clearly, and let users double-check and question the results to avoid mistakes.

People-In-Focus

Non-human

For example: animals.

Tracking technologies should prioritize non-invasive methods to minimize stress and disruption to animals' natural behaviors and habitats, ensuring meaningful data collection while safeguarding their health and welfare.

Challenge

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Input Questions:

How prescriptive should such systems be in forbidding or advising against actions that are likely to lead to statistically spurious conclusions?

This dilemma is about finding a balance between letting users explore freely and the system's responsibility to stop mistakes, in other words, how much the system should step in. questioning how much the system should step in to ensure accurate results.

Challenge

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Input Questions:

How much abstraction or approximation should we use when communicating complex ML models?

This question is about balancing making AI easy for non-experts to use while keeping it accurate, without oversimplifying and causing confusion.

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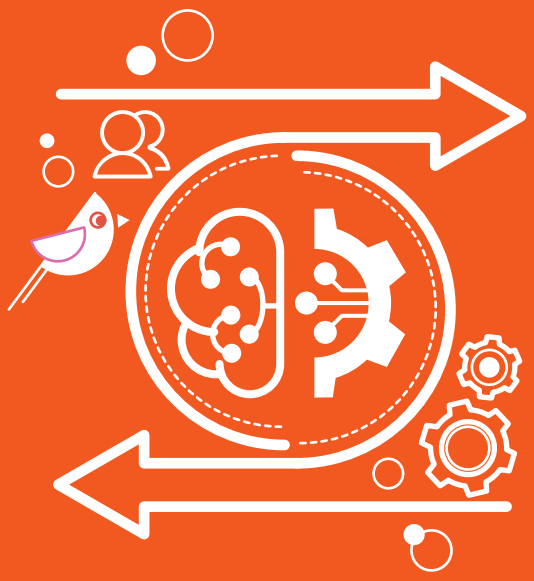

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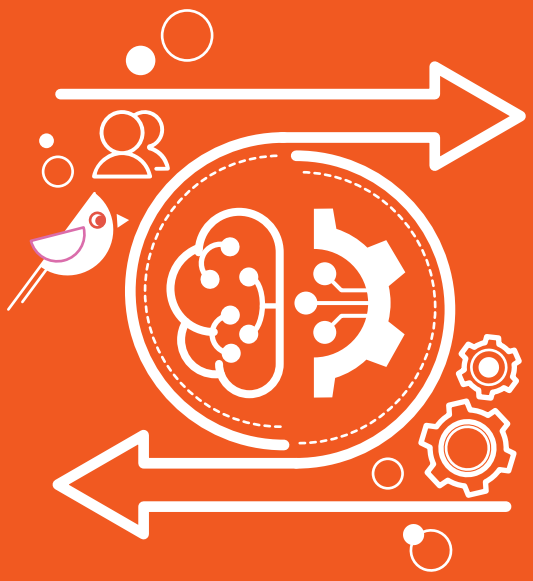

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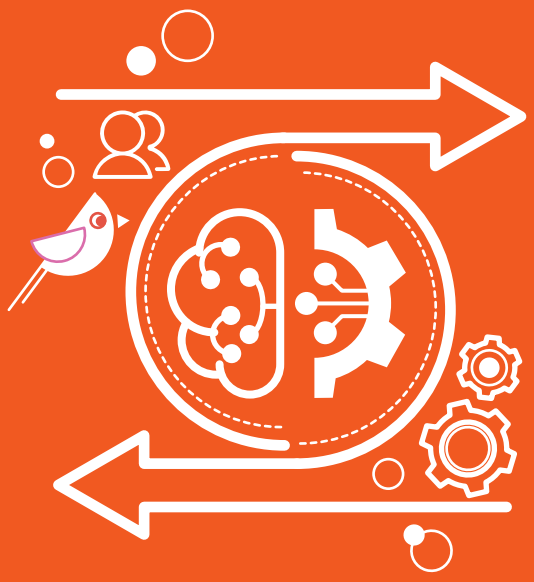

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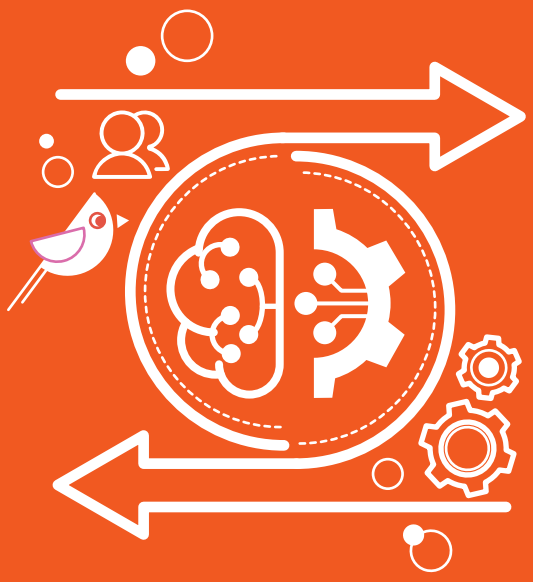

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Challenge

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Input Questions:

What standards or expectations should we cultivate when choosing to visualize algorithmic decision-making?

Balancing transparency and accuracy in ML models depends on the situation. In important areas like healthcare, it's often better to make the model easier to understand, even if it means losing some accuracy.

Challenge

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Input Questions:

How, and how many, alternate design or analytical decisions should we surface to the user?

When the data analysis process is simplified and the system doesn't clearly explain how it works, users may find it hard to tell whether they're exploring the data themselves or just being shown a ready-made conclusion. Without showing how a visualization was created, we risk spreading false or unreliable results.

Challenge

?

Input Questions:

Should we audit or structure the provenance of a visualization in order to surface irregularities?

Should the visualization process be audited to reveal inconsistencies while avoiding excessive details that might overwhelm or undermine users' ability to think critically and make their own decisions?

Challenge

?

Input Questions:

How do we visualize hidden uncertainty?

Uncertainty is a natural part of data analysis but is often hidden from users to keep things simple. To improve decision-making, we need to explore ways to show uncertainty clearly and measure how it affects users, just like we measure speed or accuracy.

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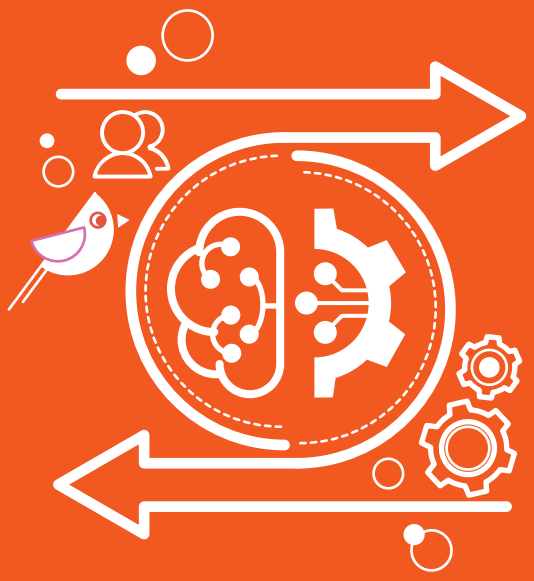

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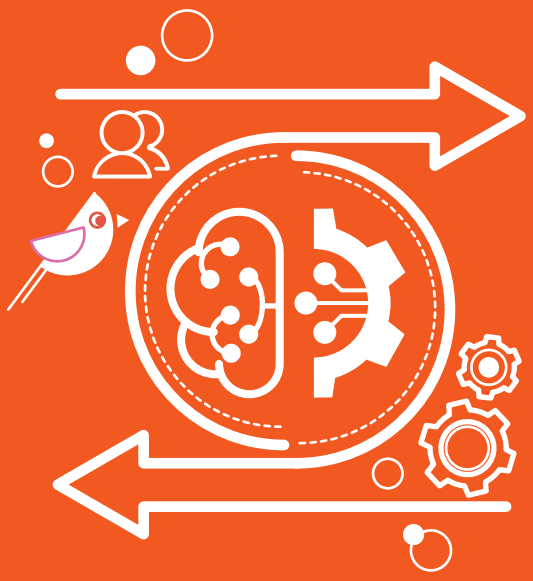

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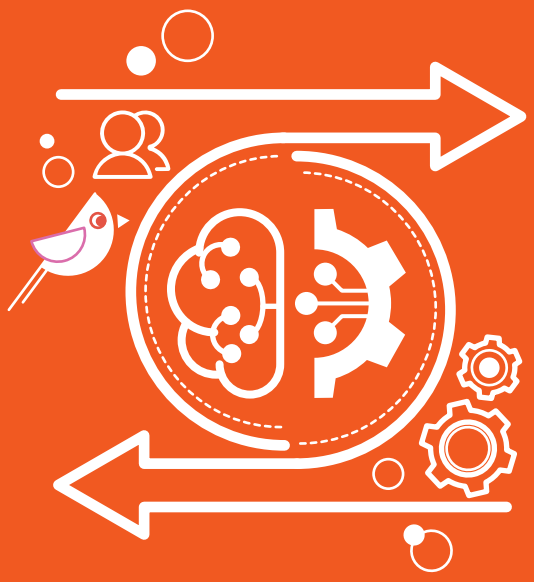

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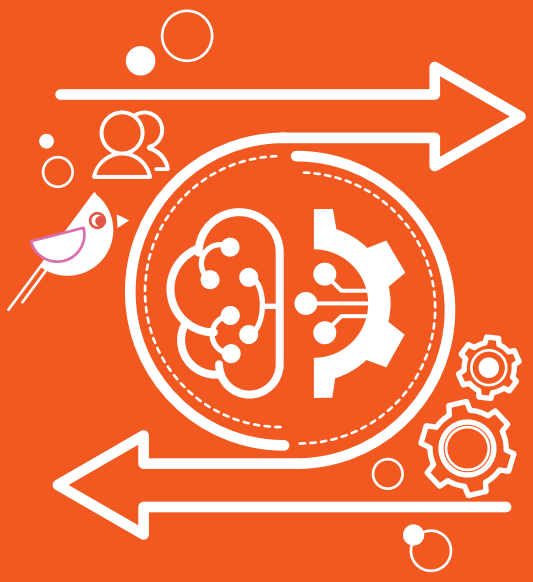

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Challenge

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Input Questions:

How to visualize hidden impacts?

What harm could arise from the system's insights, misuse, or exclusion of groups? What happens if support ends, and do the costs and efforts justify its overall positive impact?

Challenge

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Input Questions:

How to visualize hidden labor?

How can we reveal hidden work behind data, like caregivers' roles or data collection processes, to ensure responsibilities, credit, and contributions are properly acknowledged?

Challenge

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Input Questions:

How much data is "enough"?

Visualization designers should show how much data is sufficient for reliable insights, and help analysts balance accuracy and certainty in the data with simplicity and privacy protection.

Challenge

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Input Questions:

How to anthropomorphize data?

How can we design visualizations that evoke empathy for sensitive topics, bridging the gap between abstract data and the human experiences it represents?

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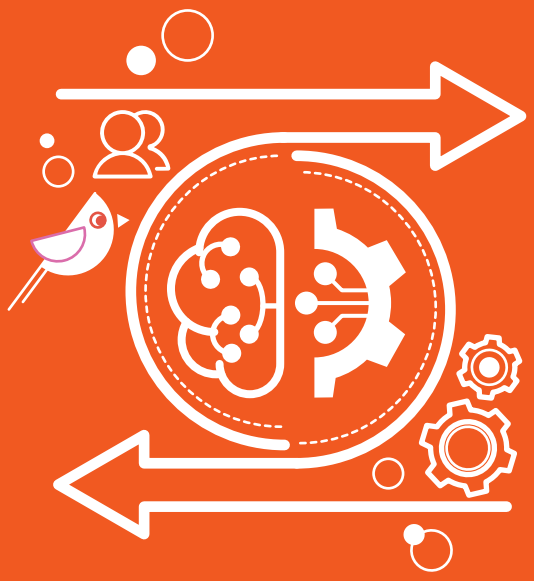

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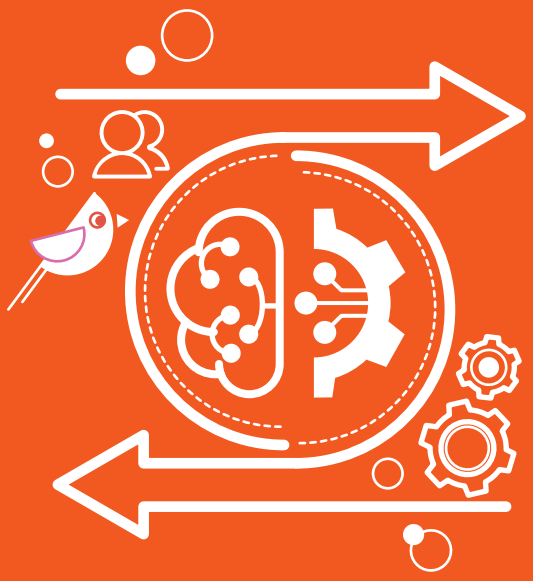

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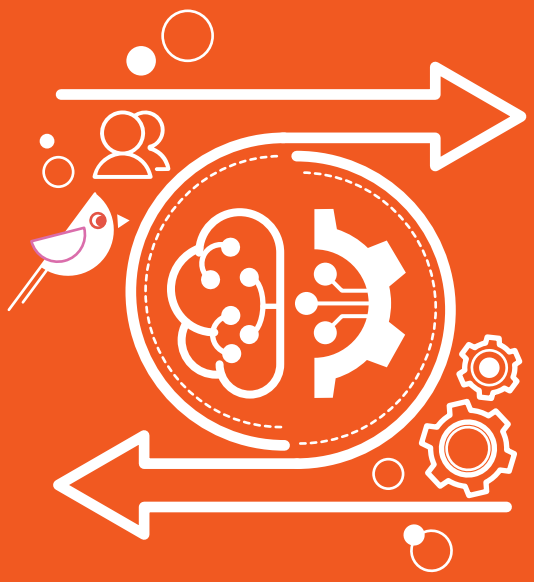

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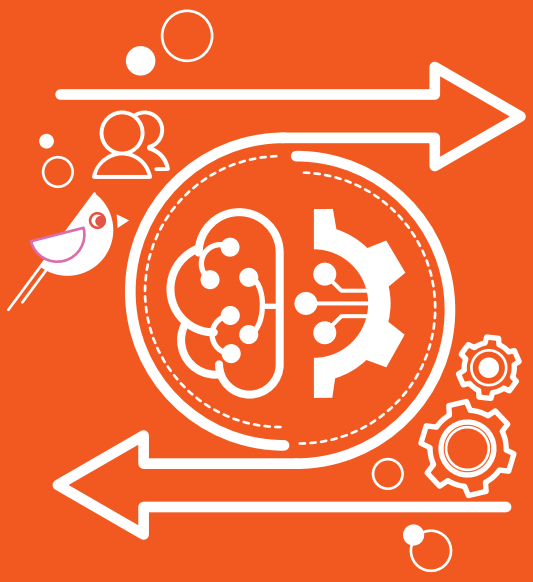

Challenge

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Challenge

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Input Questions:

How to obfuscate data to protect privacy?

Protecting the privacy and consent of individuals whose data is collected is critical. Visualizations, while revealing hidden patterns, can unintentionally expose sensitive information, leading to serious breaches of confidentiality.

Challenge

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Input Questions:

How to support data “due process”?

How can we ensure fairness and transparency in data processes, like “due process” in law, by enabling accountability, safe-guarding rights, and providing ways to challenge data-related decisions?

Challenge

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Input Questions:

Should we rethink binaries?

Should we question binary and predefined categories in data to ensure they truly reflect the complexity and diversity of the real world?

Challenge

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Input Questions:

Is diversity embraced in the process?

Does the design process include diverse perspectives, especially those outside the design team, to avoid assumptions about the ‘ideal user’ and embrace margin-alized viewpoints?

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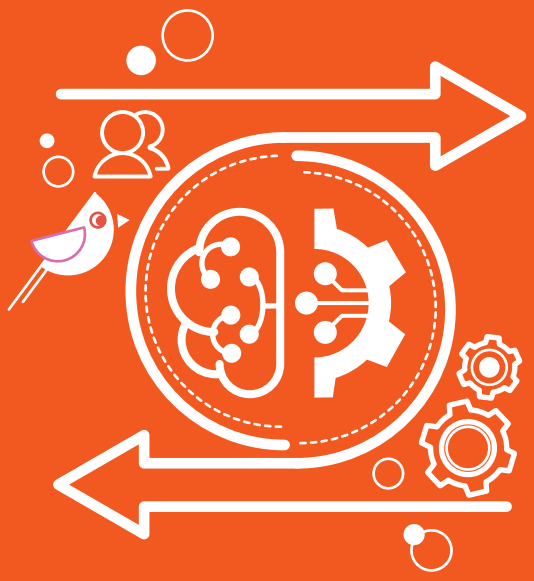

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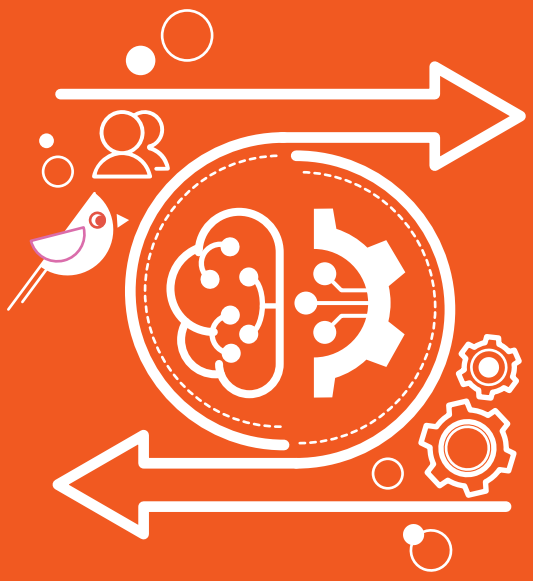

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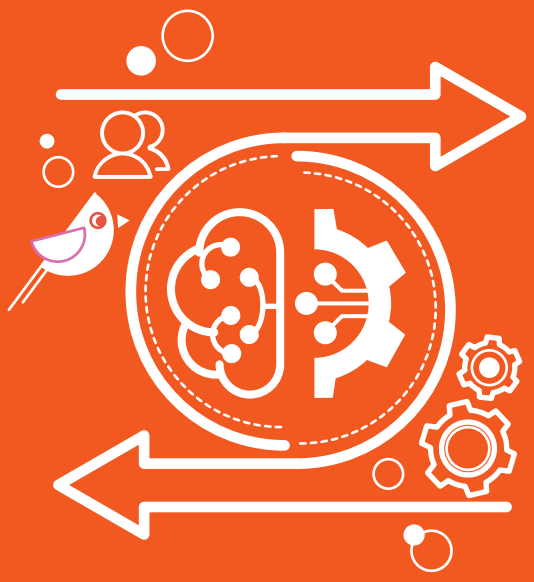
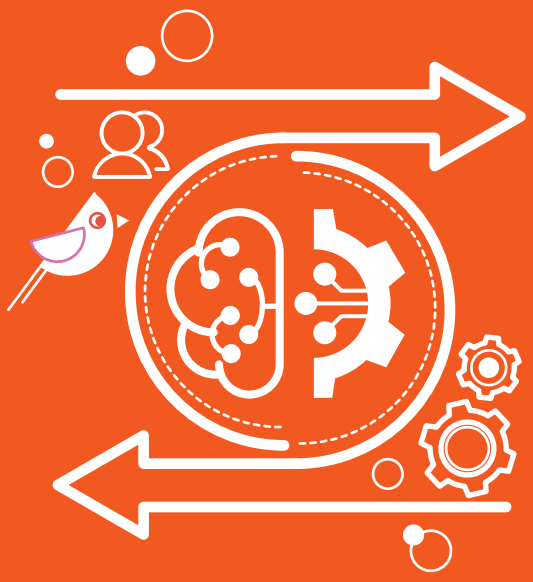


Challenge



Challenge

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Challenge

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Input Questions:

How to examine power and empower?

Who holds the power in the design process, and why? This question highlights the importance of prioritizing end users' voices to ensure their perspectives shape the project meaningfully.

Challenge

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Input Questions:

How to consider context?

How can we use human-centered and participatory design to understand end users' culture, history, and experiences, and let these insights redefine what "good" information design means?

Challenge

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Input Questions:

How to legitimize embodiment and affect, act as data advocates?

How can we use embodied and emotional experiences to make visualizations more engaging? What skills—like fine art, graphic design, or communication—do we need to balance their persuasive power while staying truthful?

Challenge

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Input Questions:

We ought to pressure or slow unethical analytical behavior.

How can we identify and address unethical practices in data analysis and visualization, ensuring strategies are in place to challenge and prevent behaviors that compromise ethical standards?

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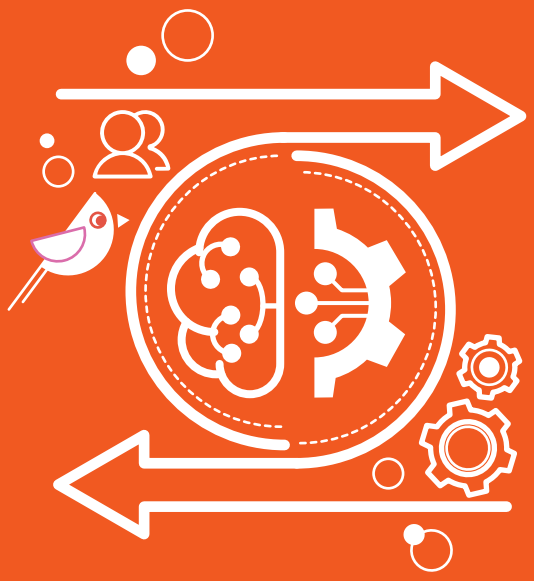

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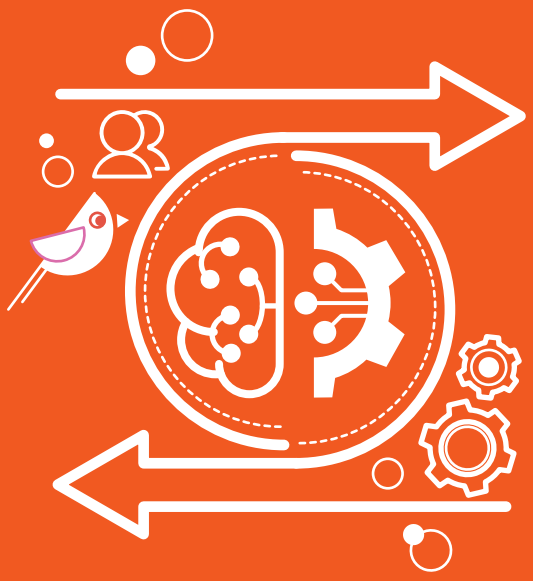

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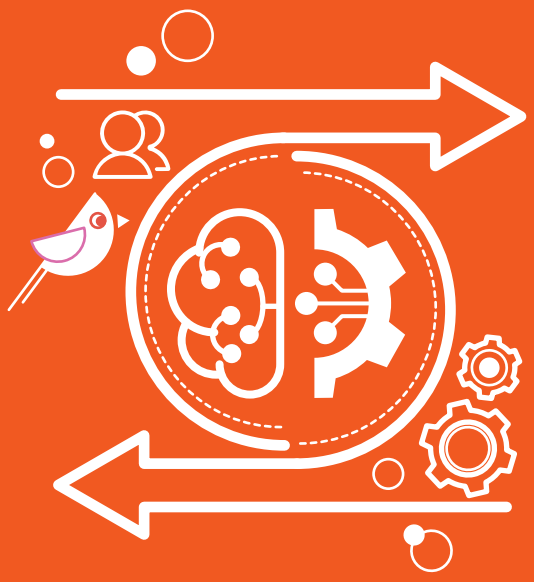

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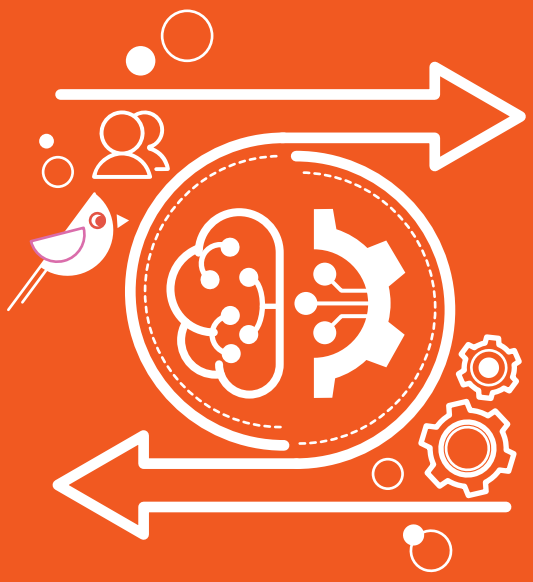

Challenge

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Challenge

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Output Questions:

Rethink binaries?

How do we show the limits of our categories in the final visualization, and how can we let users adjust or redefine these categories themselves?

Challenge

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Output Questions:

Embrace pluralism?

Can the artifact clearly show the perspectives of the researchers and designers? Whose worldview does the visualization reflect? Can it reveal whose voices are missing? Could perspective-taking help present multiple viewpoints on the data?

Challenge

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Output Questions:

Examine power and aspire to empowerment?

Can the visualization empower the end user or their community?

When might values like ‘choice’, ‘openness’, or ‘access’, intended as social goods, lead to disempowerment instead?

Challenge

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Output Questions:

Consider context?

What terminology, symbols, or cultural artifacts are meaningful to end users, and how can we integrate them into our designs? What insights might emerge from visualizing ‘messy’ data? How can we consider context when evaluating visualizations?

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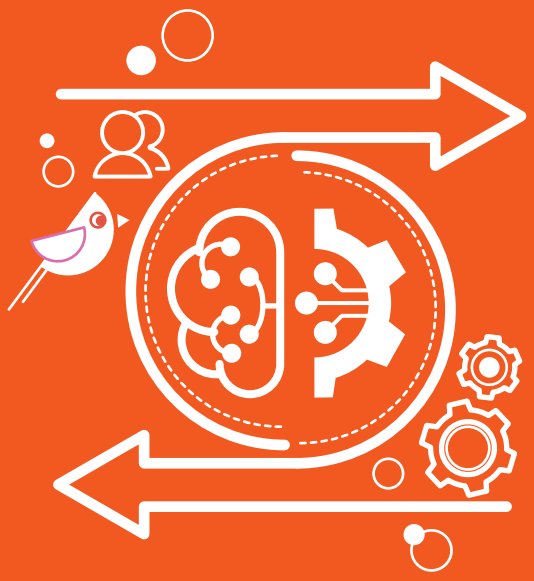

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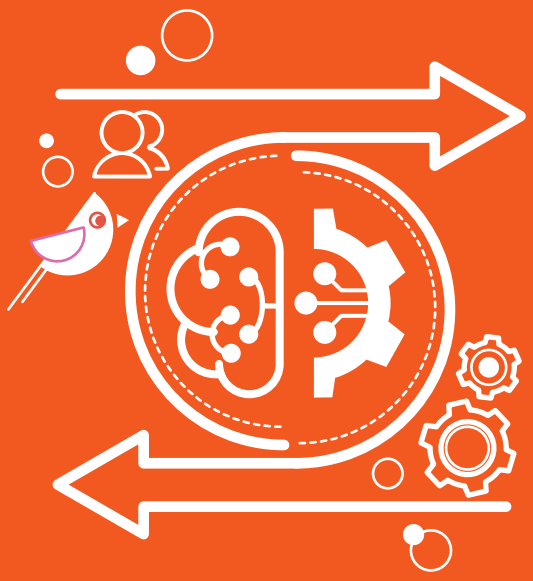

Challenge

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Challenge

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Output Questions:

Legitimize embodiment and affect?

What embodied and emotional experiences matter most to end users? Should we explore tactile, experiential, or social interactions with visualizations? Can we broaden visualizations to include formats like murals, sculptures, walks, quilts, or installations?

Challenge

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Output Questions:

Make labor visible?

Can we create a metadata visualization to show the data's origin and the stakeholders involved at each step? Have we properly credited everyone who contributed to the project?