Personal Reflection Report

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1 Introduction

The project, undertaken as part of CSE 578: Data Visualization, focused on creating an interactive visualization system to explore and communicate algorithmic bias in machine learning models. The study used advanced tools such as D3.js [1] and Scrollama.js [2] to implement a scrollytelling framework. The study compared two machine learning models—Multilayer Perceptrons (MLPs) and Kolmogorov-Arnold Networks (KANs) [3]—using datasets ADULT Census Income Dataset [4] and WESAD Dataset [5]. The project incorporated confusion matrices, grouped bar charts, custom glyph-based visuals, scatter-line plots, layered network diagrams, radar charts, and interactive features to explore the bias visually. The goal was to highlight variability in physiological signals and algorithmic fairness issues while combining interactive storytelling and data visualization techniques.

This report reflects my personal contributions, challenges, and learning outcomes during the project.

2 Project Description and Key Insights

The interactive scrollytelling system was designed to uncover and communicate algorithmic bias in machine learning models by comparing two architectures: MLP and KAN. MLPs, as a traditional feedforward neural network, are widely used for classification tasks due to their simplicity and accuracy [6]. In contrast, KANs provide a novel approach with dynamic activation functions, offering greater flexibility and adaptability [3]. The story begins with an analysis of systemic disparities observed in demographic datasets like the ADULT Census Income dataset, where gender-based income inequalities are highlighted. Visual tools such as confusion matrices and grouped bar charts were used to illustrate higher false negative rates for females, uncovering potential biases in model performance. The narrative then transitions into exploring physiological variability through the WESAD dataset, which captures multimodal stress signals such as EDA, BVP, and temperature. Glyphs were used to demonstrate demographic differences and scatter-line plots were utilized to demonstrate signal fluctuations across genders, revealing differences that may impact stress detection outcomes. Structural differences between MLPs and KANs were visually compared using layered network diagrams, where MLPs displayed static activations while KANs showcased dynamic flexibility. The story culminates with a radar chart illustrating performance trade-offs, showing that while MLPs excel in accuracy, KANs achieve balanced results across demographic groups. By progressively guiding users through these insights, the system effectively highlights the importance of fairness, interpretability, and adaptability in machine learning models.

Key findings reveal that income prediction models showed gender bias, with females more often misclassified compared to males. While MLPs performed better overall, they slightly favored one gender, whereas KANs showed fairer results across both groups but with lower accuracy. Analysis of physiological signals, like heart rate and skin activity, revealed differences between genders, which may affect stress detection. Additionally, the glyph-based visualizations provided an intuitive way to represent participant demographics, highlighting the importance of balancing fairness and accuracy in models designed for real-world applications.

3 My Contributions

3.1 Glyph-Based Custom Visualization

I created a human-shaped glyph visualization to intuitively represent participant demographics from the WESAD dataset [5]. This design effectively combined multiple features using marks and channels to enable a compact, human-centric visualization.

Color: Represented gender (blue for males, pink for females).

Brightness: Higher brightness levels represented older participants.

Height/Width: Proportional to physical attributes like height and weight.

Posture: Indicated hand preference (dominant hand).

This visualization was innovative because it combined marks (human-shaped glyphs) and channels (color, size, brightness, and posture) into a single representation, enhancing interpretability and engagement. Animated entrances and tooltips were added to provide dynamic interactivity. Users could hover over the glyphs to reveal detailed demographic insights, making the visualization both informative and user-friendly. Figure 1a shows the output, where participants' demographic features are intuitively encoded and visually distinguishable. This design simplified complex demographic data into a compact, intuitive representation.

3.2 Physiological Signal Analysis Using Scatter-Line Plots

I developed interactive scatter-line plots to analyze stress-related physiological signals, namely Electrodermal Activity (EDA), Blood Volume Pulse (BVP), and temperature over time. These signals,

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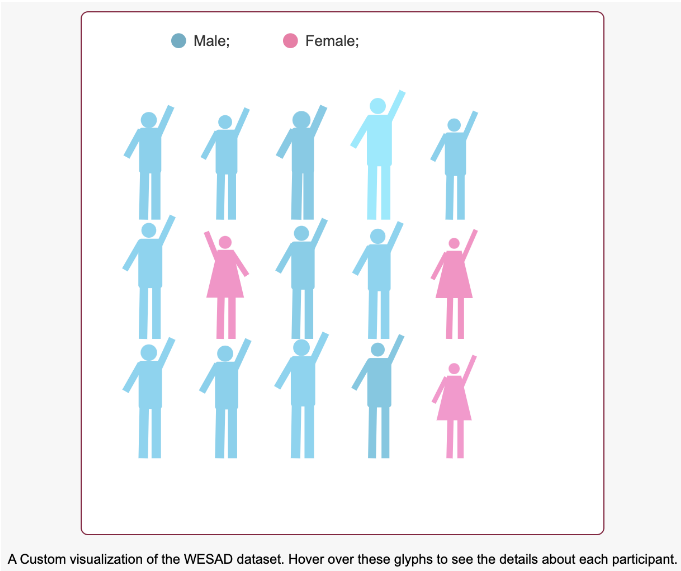
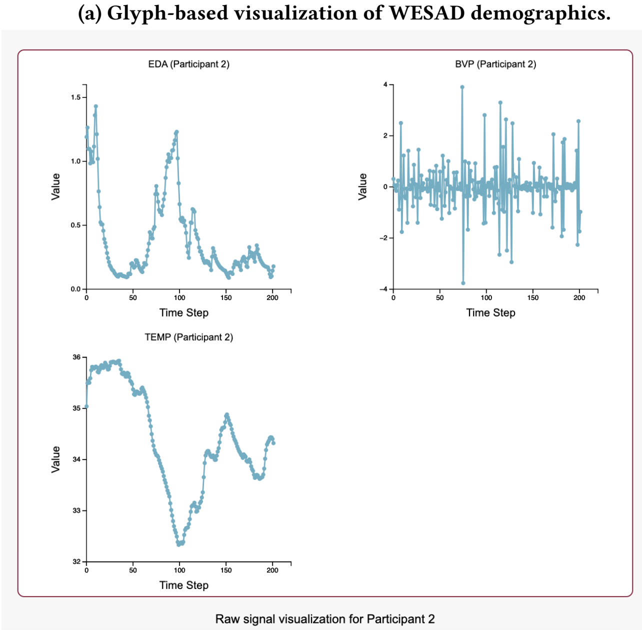


(a) Glyph-based visualization of WESAD demographics.



(b) Scatter-line plots for EDA, BVP, and temperature signals.

Figure 1: Visualization outputs: (a) Glyph-based visualization for demographics, (b) Scatter-line plots for physiological signals.

sourced from the WESAD dataset, were critical inputs for evaluating bias in the model performance.The scatter-line plots offered several advantages:

Gender-Specific Insights: Users could toggle between male and female participants to observe differences in physiological responses.

Variability Analysis: Trends and fluctuations in each signal revealed patterns influencing model performance.While analyzing the trends in physiological data, I wrote a summary in the left panel of the storytelling website for each participant to align with the scatter-line graphs, ensuring that the observations were clear and contextualized.

Tooltips: Hover features displayed signal-specific details such as minimum, maximum, and standard deviation values for better exploration of the data.

As shown in Figure 1b, BVP signals exhibited significant variability for the male participant (Blue scatter-line plots for male and pink for female). While this observation is based on a single case, it highlights the importance of investigating variability in physiological signals across gender to identify potential biases in stress detection models, a key concern for fairness evaluation.

3.3 Interactive Features and User Engagement

To ensure effective communication of complex data, I integrated my visualizations into a scrollytelling framework using D3.js and Scrollama.js. Features such as:

Animated Transitions: Visual elements entered smoothly to enhance engagement. Step-based transitions to explain each visualization interactively.

Tooltips: Hover interactions provided detailed signal or demographic insights.

Filters: Users could toggle between genders and participants to customize their analysis.

3.4 Report Writing and Documentation

I authored the project report in LaTeX, ensuring a clear, organized, and professional presentation. The report comprehensively covered all aspects of the project, including the objectives, methodology, key insights, and outcomes. I provided detailed explanations of the techniques implemented and discussed the comparisons between MLPs and KANs, highlighting their performance, fairness, and biases. Additionally, the report addressed the implications of algorithmic bias on human-centric data and emphasized the significance of fairness in machine learning models. Beyond the report, I prepared the **README file** to guide users through system setup, data preprocessing, and usage of the interactive visualizations. This ensured the project was accessible, well-documented, and easy to follow for both technical and non-technical audiences.

3.5 Additional Contributions

Beyond technical implementation and documentation, I contributed to improving the project's presentation and usability. I provided detailed feedback on the overall website design to enhance clarity, user experience, and intuitive navigation. Additionally, I worked on the poster design, focusing on effectively communicating the project's key outcomes, visualizations, and insights in a visually appealing and professional manner.

4 Challenges and Learning Outcomes

The project presented unique challenges that led to significant learning:

Mastering D3.js and Scrollama: Learning these tools required extensive self-study through documentation and tutorials.

Balancing Multiple Responsibilities: Managing deadlines alongside my PhD and other courses' commitments improved my time management skills.

Collaborating Effectively: Resolving disagreements on design choices taught me to advocate for my ideas while being receptive to constructive feedback.

4.1 Key Skills Acquired

Proficiency in D3.js and Scrollama for interactive data storytelling.

Technical writing and documentation with LaTeX.

Deeper understanding of fairness and bias in machine learning.

5 Conclusion

The project allowed me to merge data visualization and storytelling to analyze fairness in machine learning. By leveraging D3.js and Scrollama.js, I created an engaging and educational experience for users. My contributions—ranging from custom visualizations to scrollytelling integration—were instrumental to the project's success. This experience not only strengthened my technical skills but also deepened my understanding of the ethical implications of AI models.

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