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Visualizing Learning in a Social Data Science Educational Game World

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Abstract: Our poster explores visualization methods for participation in an identity-aligned, multiplayer video game world for learning data science through relationship and community building. We extend methods of representing engagement and learning in both educational games and in data science education contexts. Using simulated game play data and screen capture records of interviews with middle school girls playing an early version of the game, we explore representations for individual and multiplayer learning.

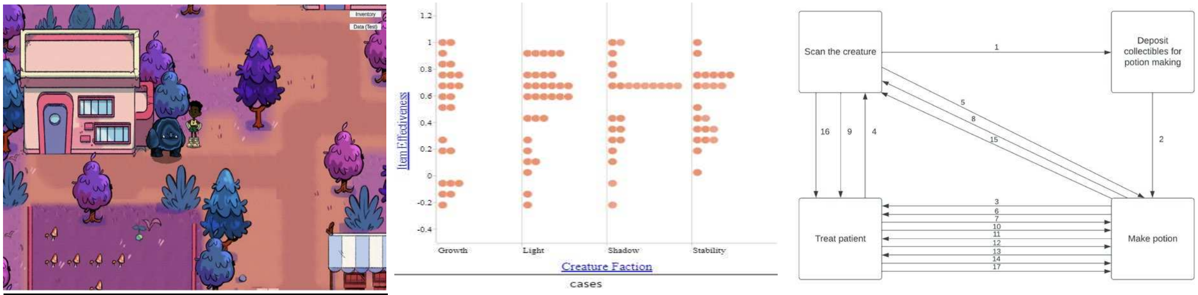
Representing learning and engagement in a virtual game world

Understanding how students learn and engage in educational virtual worlds is complex (Dawley & Dede, 2014). In this poster, we explore methods for visualizing player engagement and interactions in a virtual, social game for learning data science. Our game in development, "Isles of Ilkmaar," (Figure 1a) is a multiplayer data-rich world designed to support inclusive, identity-aligned data science learning experiences for middle school learners. Players work to rebuild community by befriending creatures and restoring the world's ecosystem balance. Players can generate, visualize, and explore game data (through a personal data log and at specific locations) to inform game activities, such as gathering resources, investigating mysteries, and crafting and giving potions, foods, and gifts to heal or befriend creatures. Here we consider ways to represent learning data science as participation in a community of social, distributed data practices (Rothschild et al., 2022, Wise, 2019). In our game, these practices involve data moves (Erickson et al., 2019) for exploring datasets generated through gameplay, such as merging, filtering, or making selections in table and visualization forms. We consider methods for understanding individual and multiplayer, community-driven data science learning in our game

Our study contributes to methods of analyzing player learning in educational games and data science learning environments. Game learning analytics typically focus on out-of-game student performance (pre-post assessments; Pellas & Mystakidis, 2020) and measuring successful in-game task completion (e.g., time to complete a puzzle correctly in Martínez et al., 2020). Virtual worlds like ours necessitate alternative analysis and assessment methods (Dawley & Dede, 2014). We seek to build on approaches like evidence-centered design that systematically gather and organize data to support claims about student capabilities, particularly in game- and simulation-based evaluations (Riconscente et al. 2016). Our approach to learning through participation calls for innovative methods for representing players' social engagement with the game world, data, and each other that move beyond pre-post assessments, self-reports, and descriptions typically used to evaluate learning in data science education environments (e.g., Lee et al., 2021). Drawing also from studies that have creatively visualized engagement with physical learning environments (e.g., Shapiro et al., 2017), we seek to develop methods for visualizing and analyzing complex, social, and distributed data science learning in a virtual world. In exploring new ways to represent learning, we also seek to develop our own engagement framework that promotes iterative design processes and qualitative development of engagement patterns, which can be assessed using learning analytics to gauge their impact on student outcomes (Mora et al., 2017). New methods and a framework will allow us to understand participation trajectories in a data community situated in the game world and hold promise for improving learning analytics and outcomes in diverse gaming and educational contexts.

Figure 1b provides an example visualization of gameplay data, showing the effects (y-axis) of giving different gift items to creatures of four different factions (x-axis). We would expect that as a player uses data to become better at gifting items to creatures, they would create and gift more items with higher item effects (like a creature's happiness or health), which would produce more items (orange dots as cases) higher on the y-axis. Such data visualizations could also reveal player preferences in gameplay, such as preferences for certain creatures (e.g., Growth tree-like creatures) or for certain item types (e.g., a player may prefer to craft and give healthy foods or treats, which have a stronger effect on mood). We are currently exploring (a) how such gameplay data, if aggregated across players, might reveal trends from a community of players collaboratively learning and participating, and (b) how showing these visualizations to players (playing in after-school groups) could support their learning by prompting their reflection on gameplay strategies or participation in and contributions to a community of players.

Figure 1
(a) "Blinded" Game World; (b) Data that Players can Generate through Play; (c) Eva's Mapped Game Activities



Using screen-capture videos of gameplay, we mapped players' transitions between activities in part of the game in which players treated sick creatures in a clinic (Figure 1c). The nodes represent key activities (scanning and sending creatures for treatment; depositing ingredients; mixing potions; treating creatures) and the arrows indicate the activity sequence (1-17). The network map, made from 15 minutes of Eva's play, highlights her gameplay strategy: while other players crafted many potions before using them to treat creatures, Eva alternated between making a potion and treating creatures before scanning new creatures to send for treatment. Distinct modes of engagement may support different ways of engaging with game data. Subsequent visualizations will include players' engagement with game data, such as when players access or explore in-game data tables or visualizations. Examining individual maps over time may indicate learning through changes in data use, while maps aggregated across players may reveal coordinated approaches to gameplay between players.

Our poster presents methods for visualizing learning in distributed, social, multiplayer game worlds. As we recruit cis-gender girls and gender expansive youth in playing the next game version in after-school groups in coming months, we are developing representations of not only individual learning but also multiplayer collaboration. Such methods can help us understand how youth's participation in our virtual world game community can motivate their pursuit of equitable, identity-aligned futures in STEM and data science.

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