Interactive Data Visualization: A Petri Dish for Intelligence Augmentation

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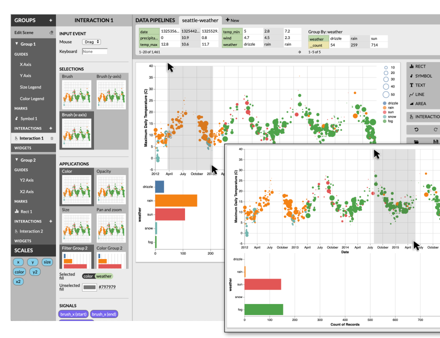
> *"To think in interaction with a computer in the same way that you think with a colleague whose competence supplements your own will require much tighter coupling between [human] and machine"* – J. C. R. Licklider, 1960

Licklider's foundational *Man-Computer Symbiosis* [7], along with Douglas Engelbart's *Augmenting Human Intellect* [3], envisages partnerships between humans and machines where the strengths of one complement the limitations of the other. This vision of symbiosis or intelligence augmentation is receiving renewed attention in the face of rapid advances in artificial intelligence and machine learning — while models can help scale human effort and mitigate our cognitive biases, humans remain key for adapting models to the complex and ever-changing sociocultural landscape. **My research group examines the substrate of this interactive loop: the design of the computational representations that mediate interactions between people and machines.** On the human side, these representations form the nouns and verbs of user interfaces, and shape what we perceive to be possible with a (graphical or textual) interface. On the machine side, these representations impact how tractable it can be for algorithms to reason about tasks or domains. Thus, **we study how these representation should be designed, explore the intelligence augmentations they enable, and more richly characterize and expand who these representations serve.**

My research investigates these issues in the domain of interactive data visualization. From scientific discovery to business intelligence, journalism, and public policy, society has increasingly embraced visualization as a critical medium for recording, analyzing, and communicating data. And, the human-computer partnership of intelligence augmentation is central to visualization: people use visualizations to interactively make sense of data and inspect algorithmic processes, while automated methods can suggest effective visualizations and unobtrusively optimize processing. Moreover, through its formal models (e.g., scales of measure for input data, SQL for data transformation, and grammars of interactive graphics), visualization provides a conducive structure for more systematically exploring the design, engineering, and sociotechnical implications of intelligence augmentation.

DESIGNING COMPUTATIONAL REPRESENTATIONS FOR INTELLIGENCE AUGMENTATION

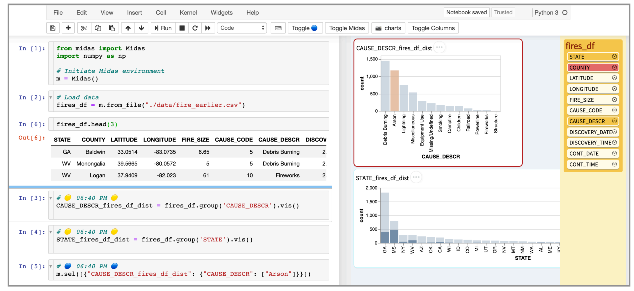
My PhD work contributed two declarative models for specifying interaction techniques within data visualizations: **Reactive Vega** [14, 15], an expressive low-level representation that extends techniques from functional reactive programming and streaming databases; and **Vega-Lite** [13], a concise and higher-level grammar that enables systematic enumeration of interaction techniques. These models **have been widely adopted** in data science (e.g., via the Altair Python package [18]), in industry (e.g., at Apple, Google, and The LA Times), and in academic research, and my group uses them **as platforms for further research** on how their design enables intelligence augmentation.



A user demonstrates a cross filtering interaction in Lyra 2.

For instance, with **Lyra 2** [21], my students and I studied how designers can construct interaction techniques *by demonstration* (i.e., by performing mouse clicks or drags on the visualization directly) rather than through textual specification. Heuristics parse these demonstrations to enumerate candidate Vega-Lite specifications and populate a sidebar of thumbnail suggestions. Users can select suggestions, preview and test them live, or refine them through additional demonstration. In the sidebar, Lyra also exposes *signals*: reactive variables that drive interactive behaviors found in the lower-level Vega language. Through drag-and-drop operations, these signals can be bound to the properties of visual elements to author custom interaction techniques that would not have been expressible with Vega-Lite alone (e.g., labeling the corners of a brush). Thus, with Lyra 2, users no longer need to explicitly select an abstraction level to work with. Rather, the system reasons about the affordances of the two levels and bridges between them based on user interaction: Vega-Lite's high-level primitives make it a suitable target for rapidly producing recognizable output via demonstration, while Vega's lower-level design enables fine-grained customization fit for sidebar property inspectors.

Similarly, with **B2** [20], my collaborators and I developed mechanisms to tighten the feedback loop between coding and interactive analysis in computational notebooks. Instead of requiring data scientists to manually specify visualizations, B2 instruments data frames to automatically synthesize corresponding visualizations. This step leverages Vega-Lite's high-level design as marks and visual encodings are inferred from the data types of data frame columns, and interactive selections are added by analyzing data frame lineage (e.g., a cross filtering interaction between two visualizations whose data frames share a common ancestor). The resultant visualizations are displayed in a sidebar dashboard, rather than interleaved with code in the notebook, to facilitate richer multi-view coordination. And, to ensure that analysts can act on and reproduce the results of interactive analysis, B2 reifies interactions as data frames, and maintains an interaction log in a code cell. Here, too, Vega-Lite plays an important role: by modeling interaction techniques as *selections*, or declarative data queries, interactions can be reified and logged in semantically meaningful ways (i.e., by referencing data fields and values rather than low-level events and properties).

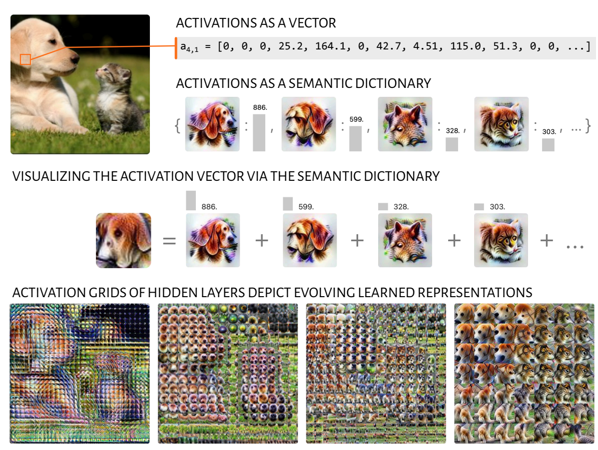

B2 bridges computational notebooks and interactive dashboards by using Vega-Lite's interactive selection as a *shared representation*.

This thread of work points a way forward for intelligence augmentation: **layered, declarative domain-specific abstractions can provide a shared representation** for people and machines to collaborate around. Declarative domain-specific models allow both sides of intelligence augmentation to reason about tasks in more semantically meaningful ways — for example, allowing users to focus on visualization design concerns rather than implementation details, while allowing systems to reason about data types and provenance to optimize processing. Critically, layering these models helps diffuse the classic tension between ease-of-use and expressivity: both people and systems can choose a level of abstraction suited for the task at hand and, as Lyra 2 demonstrates, fluidly move between them as needs change. In ongoing work, my group is unpacking the implications of these insights by exploring wider portions of the visualization design space (e.g., for distributed data and asynchronous events under review at VIS 2022 [19], and unifying models of animation and interaction in preparation for EuroVis 2022) as well as **generalizing our approach** to interactive web applications (a first submission is planned for ACM CHI 2022).

UNCOVERING NOVEL ABSTRACTIONS VIA MACHINE LEARNING INTERPRETABILITY

While promising, the models above have required several PhDs worth of effort to craft for just a single domain — an approach that will not scale for widespread adoption of intelligence augmentation in a diverse range of domains. Thus, in parallel, my group is turning to neural-based machine learning (ML) models. While these models are demonstrating astonishing capabilities by learning patterns from large-scale datasets, deploying them is fraught with risk because it is difficult to determine what these patterns are, audit them in cases of model failure, or ensure they align with values of fairness and equity. Accordingly, my group investigates how visualization can be used to inspect the representations ML models learn, enabling users to build trust in or even learn from them.

By default, learned representations are expressed too abstractly to map onto domain semantics — in computer vision, for example, models represent images as high-dimensional data cubes, where each cell is an *activation* or the amount a neuron fires due to the input. My collaborators and I have shown [11] how an optimization process, that perturbs an image of random noise in order to maximally activate the representation, can transform the data cube into a *semantic dictionary:* instead of abstract indices, activations now map to to visual icons that surface human-salient concepts (e.g., "floppy" and "pointy" ears as shown in the figure). This dual expression — activations as mathematical or visual constructs — affords a rich, compositional design space. For instance, we can jointly optimize the entries of the semantic dictionary to depict the activation vector, repeat the process across the image to yield an "activation grid" and combine this grid with feature attribution techniques to reveal which learned representations are most responsible for the model's output. Our exploration suggests **opportunities to formalize this design space**, akin to user interface toolkits and grammars of graphics, such that users can assemble their own, custom interfaces to interpret their ML models rather than relying on monolithic

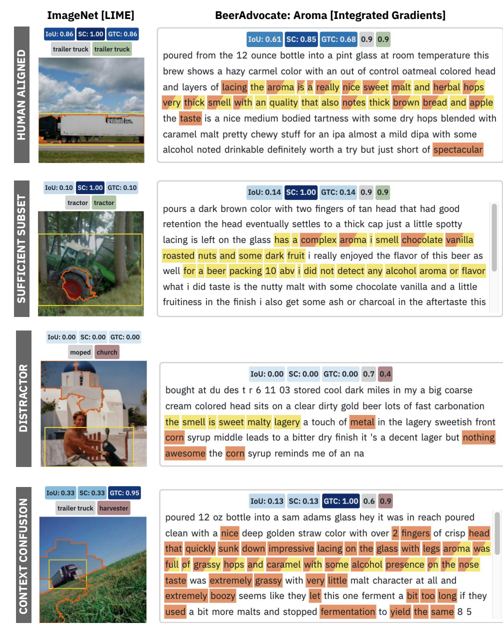


Through interface sketches, we explore the affordances of treating machine learned concepts as both mathematical and interface constructs.

tools. However, there are also limitations with our approach: arguably, the semantic mapping is occurring largely because the domain (computer vision) is aligned with our perceptual system, rather than due to specific interface design choices. And, as a result, these interfaces require substantial manual inspection — to turn up examples for our perceptual system to attend to — which occurs in an ad hoc fashion and can yield cherry-picked results.

To address these concerns, my students and I are developing methods that are agnostic to input modality and structure the process of interpretability so that the burden of mapping semantics does not fall entirely on the human. For example, the **Embedding Comparator** [1] calculates a similarity score to compare pairs of embedding models (i.e., models that map high-dimensional discrete input to lower-dimensional continuous vector spaces). This score computes the *reciprocal local neighborhood* of every embedded object (i.e., how many of an object's nearest neighbors are shared between the models or are unique to a model), and uses this score to organize and visually encode interface elements (e.g., color-encoding projection plots and sorting local neighborhood visualizations). Our user studies show that our score-based approach allows participants to more broadly and deeply explore embeddings, and thus have more confidence in their insights, as compared to their existing Jupyter-based workflows.

Similarly, with **Shared Interest** [2], we have developed a set of metrics to measure the alignment between human-annotated ground truth and model behavior (as determined by *saliency*, or scores for each input feature that indicate its importance for the model's output). These metrics, analogous to precision and recall for model performance, help reveal eight recurring patterns of model behavior across computer vision and natural language classification (four patterns are shown in the figure). Through case studies, we demonstrate how these metrics can be composed together within a visual analytics workflow to enable more systematic analysis of model behavior. For instance, a board-certified dermatologist used Shared Interest to rapidly identify lesion types that the model was *"obviously [doing] a pretty good job [with]"* but that they *"would discard the model"* for lesions that exhibited a "scalloped border." Perhaps most interestingly, Shared Interest helped the dermatologist find cases where the model relied on both the lesion and surrounding skin to make a prediction, causing them to wonder if *"[the model] is seeing something we're not truly appreciating in the clinical image [...] Maybe there's really subtle changes we're not picking up that it is able to."*



4 (out of 8) recurring model behavior patterns across two modalities (vision and text) identified via Shared Interest (model saliencies in orange, human annotations in yellow).

Although these first two research threads have been unfolding independently, I am building towards a future where **machine-learned representations help bootstrap the design of expert-crafted symbolic representations**. To do so, however, we not only need to discover *what* the learned representations are (i.e., the focus of my current work) but also what their *functional role* in the decision space is. Thus, my group's ongoing work **broadens our focus on interpretability along two axes**. First, we are moving beyond purely exploratory interfaces and towards more *collaborative* ones, where a person manipulates learned representations to build intuition for how they operate. Here, our initial results seem promising — by perturbing model inputs in semantically-meaningful ways, we found that 14 physicians were able to identify (mis)alignments between model behavior and clinical concepts [17]. Along the second axis, we look to shift interpretability to earlier phases of the ML pipeline (i.e., from "post hoc" interpretability to interpretability during model training). In doing so, how might we not only observe learned representations emerge and evolve over training epochs, but also intervene and steer the model's learning in more granular ways than active learning approaches have considered so far?

WHO ARE THESE REPRESENTATIONS DESIGNED FOR?

The third strand of my research examines the *socio*technical implications of my technical work. In collaboration with two other teams of researchers, my group and I **critically reflected** [12] on our work on visualization tooling to surface assumptions we had implicitly made about our target end-users. In particular, intelligence augmentation research is often wrapped in the language of "democratization" (i.e., making expert workflows available to the broader public). But, in doing so, we realized that we were losing important nuance when thinking about data literacy and expertise. For example, although our tools focus on enabling visualization design without programming, they require data to be structured in specific ways which, in turn, requires users to engage in non-trivial computational thinking. This simplistic conceptualization of expertise recurs in the context of ML interpretability as well, as end-users are often bucketed into three categories: ML experts, domain experts, or "non-experts." To bring more nuance to characterizing stakeholders, my group drew on the literatures in pedagogy, critical theory, and participatory design to contribute **a more granular treatment of user expertise and needs** [16]. We decompose expertise into types of knowledge (formal, instrumental, personal) and the contexts they may manifest in (ML, data domain, and the general milieu) to yield a *generative* framework to inform future interpretability research. For instance, our framework helps identify opportunities to leverage instrumental knowledge to up-skill workers in new domains via ML, as well as the ways in which people with personal knowledge in the milieu (seeming "non-experts" under prior approaches) can contribute rich "on-the-ground" information to help debug model failures.

My group's **study on COVID-19 visualizations** [6] has further highlighted the pressing need for researchers to treat data literacy and expertise with nuance. By analyzing 41,000 visualizations discussed across 500,000 tweets, and through a 6-month digital ethnography of coronavirus Facebook groups, we discovered how COVID-19 skeptics have been marshaling data science and visualization to argue *against* public health guidance (e.g., mask mandates and lockdowns). Contrary to the temptation to describe this phenomenon as "anti-science," we found that Facebook group members engaged in meticulous data-driven discourse and citizen science — encouraging one-another to "follow the data", critically assessing data sources and representations in the style of academic peer review, and conducting livestream tutorials for downloading and wrangling public health data. Moreover, the "counter visualizations" these groups produce do not fit easy "chart junk" caricatures but are often so highly polished as to be right at home in scientific and journalistic publications or health department records. **Our findings expose urgent tensions** in research on data visualization and intelligence augmentation (including my own). Binary categorizations of literacy/illiteracy (or expert/non-expert) do not capture these groups' skillful manipulation of data and, arguably, our use of "democratization" hinders us from grappling with how intelligence augmentation may be contributing to the problem — how might our work, by making expert practices broadly accessible, be facilitating a devaluing of expertise? Ever-more "expressive" tools or even error checkers [5] are unlikely to ameliorate matters significantly until they shift towards considering knowledge as *"multiple, subjective, and socially constructed"* [10].

Finally, my research has also begun to work with blind and low-vision people — a population that has been underserved, at best, by data visualization. After my students engaged in a collaboration with *The Perkins School for The Blind*, we distilled a series of **sociotechnical considerations for accessible visualization** [8] including being attentive to how research novelty may be in tension with the often "low tech" interventions that a disabled population might most benefit from, and ensuring that research participants with disabilities are compensated to reflect their specialized skills (e.g., with reading braille or using a screen reader). To operationalize these considerations, we are exploring **alternate modalities** for representing data. Although we have investigated haptics [4], we have found **natural language to be especially promising** [9] — we collected and analyzed 2,000 visualization captions to identify four level of semantic content. Evaluating the usefulness of sentences at every level with 30 blind and 60 sighted individuals reveals similarities and stark differences: while both groups generally prefer mid-level semantic content, they diverge sharply at the lowest and highest levels.

#	Descriptor	Semantic Content	Example
4	Contextual	causal inferences, cultural relationships, current events	*"The big drop in prices was caused by financial crisis of 2007–2008."*
3	Perceptual & Cognitive	complex trends/patterns, common concepts, "natural" articulation	*"There was a gradual stair-shaped rise in the interest rate between 2005 and 2006"*
2	Statistical & Comparative	descriptive statistics, extrema, outliers, correlations, etc.	*"GOOG has the greatest price over time. MSFT has the lowest price over time."*
1	Elemental & Encoded	chart type, encoding channels, title, axis ranges, labels, colors	*"This is a multi-line chart that plots price (0 to 800) by date (2000 to 2010).*

A four-level model of semantic content for accessible visualization via natural language description [9].

Our ongoing work builds on these insights by improving support for screen readers in the Vega stack and investigating neural methods for automatically generating level 3 captions. Like most assistive technology, I anticipate that successful outcomes here will yield benefits that extend beyond people with disabilities (also known as the "curb cut effect"). In particular, I believe advances in accessible visualization will help us **raise the level of abstraction of visualization research.** For instance, improving screen reader support is likely to impose pressures on grammars of graphics that may yield even higher-level task- or insight-oriented grammars. Similarly, were our ML model able to produce reasonable level 3 captions, it would suggest that the model had learned representations of the *cognitive* tasks sighted people perform when reading visualizations. If so, we should be able to repurpose these representations for other tasks — for example, recommending *insightful* visualizations rather than simply *valid* ones like current recommender systems. Much like the "visual encoding" abstraction has enabled systematic study of what visualizations *look* like, I expect accessible visualization research will yield abstractions that facilitate deeper study about what visualizations *mean*.

RESEARCH IMPACT

The visualization software my research has contributed is open source and widely used in the tech industry (e.g., at Google, Apple, and Microsoft), in journalism (e.g., at the LA Times), by the Jupyter and Observable data science communities, and has been deployed on Wikipedia. I have prioritized broad communication of my research results and thus have spoken to academic audiences outside my immediate communities (e.g., keynotes or invited talks at an ACM SIGMOD workshop and the American Statistical Association's SDSS conference) as well as at practitioner venues (e.g., OpenVis Conf and the U.N. Data Viz Camp). My group also published an interactive article of our COVID-19 study results; it has repeatedly gone viral on social media and has been read by almost 20,000 people in 4 months. My work has been recognized through Best Paper awards and nominations, an NSF CAREER and Google Research Scholar Award, and I have been named a Kavli Fellow by the National Academy of Science.

TEACHING STATEMENT

At MIT, I have contributed to teaching in severals ways. I have developed a new graduate course *6.859: Interactive Data Visualization* (previously numbered 6.894) that mixes traditional lectures with active learning techniques and interactive studios to increase student engagement and improve performance. The class prioritizes grappling with the ethical implications of visualization via an individual assignment, several readings, as well as a lecture session comprising think-pair-share activities and small group discussions. It attracts students from a diverse range of disciplines including computer science, architecture, design, urban studies and planning, and the Business School. Enrollment has grown from 50 to 128 in its most recent (third) offering, and students in the class nominated me for MIT's *Teaching with Digital Technology Award*. Class materials were featured on the front page of *Hacker News*, and are being used at Stanford University, the University of Washington, and the Université Paris-Saclay.

I also co-instruct *6.170: Software Studio*, an undergraduate course on engineering interactive web applications, with Prof. Daniel Jackson. I helped redesign the course to place greater emphasis on user-centric design methods and analyzing the the ethical implications of software and user interface design. This broader focus has reinvigorated enrollment, which had dropped to a low of 56 the year I began and has now rebounded to 98. Based on this work, Prof. Jackson and I were invited to participate in the MIT College of Computing *Dean's Action Group on Active Learning Projects*, and for my work across both classes, I received the department's ***2020 Kolokotrones Education Award.***

Finally, my PhD students and I have mentored 18 undergraduate and Master's students. These students have been co-authors on our research publications, have helped to republish our COVID-19 study results via an interactive article, and have contributed to our open source software projects including Vega-Lite and Lyra.

SERVICE STATEMENT

I have served my communities in various roles including by organizing the bi-weekly MIT CSAIL HCI Seminar, serving on the program and organizing committees for academic and practitioner conferences (e.g., IEEE VIS, ACM IUI, OpenVis Conf, and Information+), and as a co-editor for the Distill journal. The bulk of my service, however, has been devoted to broadening participation in computer science. In the MIT EECS department, I serve on the *Committee for Diversity, Equity, and Inclusion* and the subcommittee interviewing inaugural Diversity Officer candidates. Through MIT's *Summer Research Program*, which provides research pathways for students from minoritized or underserved backgrounds, I am mentoring an undergraduate intern whose work is planned for an ACM CHI 2022 submission. For my efforts, the department awarded me the ***2021 Seth J. Teller Award for Excellence, Inclusion and Diversity***. Finally, for my academic community, I have twice served as the *Diversity & Inclusion Co-Chair* for IEEE VIS, and helped grow our diversity scholarship program to reach students across Latin America including in Brazil, Colombia, Mexico, Peru, and Puerto Rico. I now serve on the *IEEE Ad Hoc Committee on Diversity & Inclusion*, tasked with making recommendations to promote diversity and inclusion across all IEEE conferences.

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