Editor:
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Visualization Collaborations
What Works and Why

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In 1987, Bruce McCormick and his colleagues outlined the current state and future vision of visualization in scientific computing.[1] That same year, Donna Cox pioneered her concept of the "Renaissance team"—a multidisciplinary team of experts focused on solving visualization problems.[2] Even if a member of the visualization community has never read McCormick and his colleagues' report or heard Donna Cox speak, he or she has probably been affected by some of their ideas.

Of particular interest to us is their vision for collaboration. McCormick and his colleagues envisioned an interdisciplinary team that through close interaction would develop visualization tools that not only were effective in the context of their immediate collaborative environment but also could be reused by scientists and engineers in other fields. McCormick and his colleagues categorized the types of researchers they imagined constituting these teams, one type being the "visualization scientist/engineer." They even commented on the skills these individuals might have. However, they provided little guidance on how to make such teams successful.

In the more than 25 years since the report, researchers have refined the concepts of interaction versus collaboration,[3] interdisciplinary versus multidisciplinary teams,[4,5] and independence versus interdependence.[6] Here, we use observations from our collective 18 years of collaborative visualization research to help shed light on not just the composition of current and future visualization collaborative teams but also pitfalls and recommendations for successful collaboration. Although our statements might reflect what seasoned visualization researchers are already doing, we believe that reexpressing and possibly reaffirming basic collaboration principles provide benefits.

Scientific Interaction, Exchanges, and Collaboration

Scientific interaction is some form of communication between researchers. At the lowest level, these interactions might consist of merely passing data, but they can extend to a higher-level expression of information and ideas. *Scientific exchanges* are when two or more researchers interact in a way that affects one or more of the researchers' trajectories. Although scientific exchanges frequently occur between researchers in the same discipline, here we focus on exchanges between researchers in different disciplines.

One common exchange is when a visualization researcher with a new method requires realistic data on which to test her ideas. She obtains data from a colleague in another discipline, tests the method on the data, and produces images that she (possibly) provides back to her colleague. As the visualization researcher works with the data, she develops new ideas for improving the method, which she then pursues independently of her colleague. The final results are published at a visualization venue. Figure 1a depicts this scenario.

Collaboration is a special type of scientific exchange in which researchers co-labor toward a common set of goals in a way that affects all their individual research trajectories. This set of goals might contain individual, disciplinary goals expressed by each participant; what makes them common is that the group has become vested in seeing them all accomplished. The interactions in collaborative exchanges are bidirectional; collaborations often emerge from more general exchanges that become bidirectional. In our previous example, if the colleague altered his research trajectory on the basis of the images the visualization researcher passed to him, and the two established a set of common goals, the ex-

 Published by the IEEE Computer Society

change would become a collaboration. Figure 1b depicts this scenario.

Visualization collaborations often take place between visualization researchers and researchers in other areas. As part of a team seeking to solve a common set of goals, visualization researchers help domain experts organize, categorize, present, and explore their data. These common goals will include research interests that lie in both the application domain and visualization, with team members committed to them all.

Interdisciplinary versus Multidisciplinary

As we mentioned before, since McCormick and his colleagues' report, many different areas such as the medical sciences have closely examined the distinction between "interdisciplinary" and "multidisciplinary." We admit that the descriptions' nuances hinge on a person's definition or concept of a particular scientific discipline. However, we think that considering the possible definitional distinctions is relevant here because both types of teams appear in the visualization community.

An *interdisciplinary team* tackles problems lying in a space of science where a discipline gap exists (hence "inter"-disciplinary).[7] These problems require a hybrid approach that draws from multiple disciplines. Interdisciplinary teams tend to collaboratively set the endeavor's goals, which might only tenuously connect back to the individual researchers' disciplines. The members are equal partners in terms of the workload and responsibility and are equally entitled to the accomplishments. This mode of research can lead to the establishment of a new discipline—computer science is one such field that grew out of researchers working in the gap between applied mathematics and electrical engineering.

A *multidisciplinary team* tackles problems that have questions and challenges that lie in distinct disciplines but require the confluence of disciplinary expertise. These teams are discipline-oriented: all the researchers work in parallel with clearly defined roles and specific tasks that provide added benefit to their disciplinary goal. Multidisciplinary research tends to refine and expand established disciplines over time. Visualization is an example of an established discipline that has been heavily influenced and expanded by collaboration with experts in fields such as design, cognitive science, and statistics.

A third category is emerging: *intradisciplinary teams*, which are a consequence of a discipline's expansion. Once a discipline becomes sufficiently large in its coverage of scientific topics, a researcher can no longer be expected to have expertise across

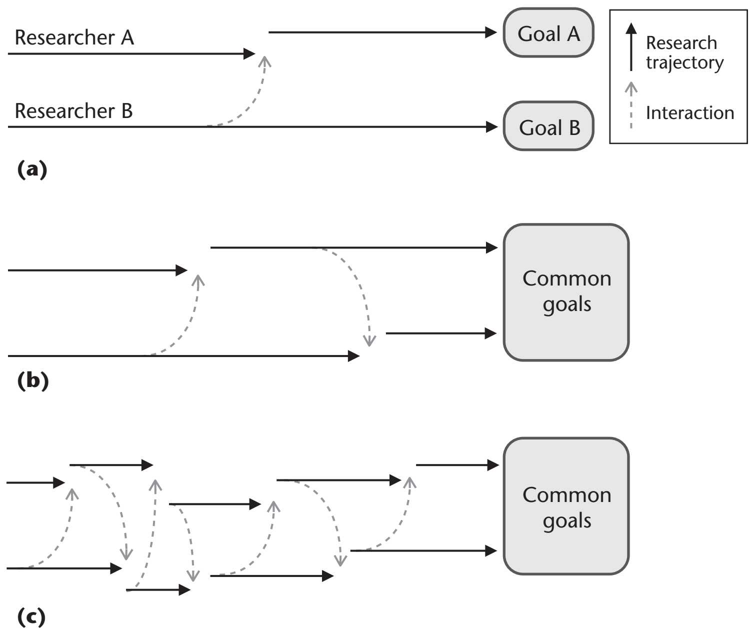

Figure 1. A range of scientific exchanges. (a) An exchange in which one researcher alters his or her trajectory on the basis of a scientific interaction; the researchers are working toward different goals. (b) A collaborative exchange with bidirectional interactions that alter both researchers' paths as they work toward common goals. (c) An interdependent collaboration that relies on many interactions between the researchers to reach common goals.

it. In this case, intradisciplinary teams can develop in which researchers in the same discipline but with different, complementary skills interact. These teams' characteristics might match either the interdisciplinary or multidisciplinary pattern, depending on the nature of the collaboration. The growth of topics and researchers in the visualization community has led to intradisciplinary visualization teams.

Visualization Collaborative Teams

According to McCormick and his colleagues, interdisciplinary research teams comprised five types of members:

- computational scientists and engineers,
- visualization scientists and engineers,
- systems support personnel,
- artists, and
- cognitive scientists.

These roles and their associated disciplines have evolved significantly since the report, and the boundaries between these disciplines have softened.

So, we propose an updated list of the roles and skills of members often found on collaborative teams that focus on visual data analysis. The first two roles (domain expert and visualization expert) are the primary ones. Each of the other, secondary roles (in no particular order) is either assigned to a team member dedicated to that role or assumed by a primary member when necessary.

Domain Experts

Visualization system users are no longer limited to the sciences and engineering. For example, economics, business, and the humanities are all turning to data and visualization to gain insight. So, we broadly define domain experts as researchers who use visualization tools to perform complex data analyses.

In the visualization community, interest is increasing in the design and implementation of studies evaluating visualization tools' efficacy.

Visualization Experts

The knowledge and expertise for effectively encoding data visually and building interactive, exploratory systems are no longer restricted to the realm of computer science. Experts from fields such as design and the sciences are developing visualization systems to explore data. Visualization expertise includes skills in human-centered design, evaluation, perception, cognition, statistics, and high-performance computing. Visualization experts are now responsible for everything from characterizing problems to designing, developing, and evaluating tools.

Designers and Human-Computer-Interaction Experts

An increasing awareness of the importance of user-centered design, as well as the vital importance of functionality and usability, has led to the inclusion of designers and human-computer-interaction experts on these teams. Often, the visualization expert assumes this role. However, sometimes these experts are brought onto the team to explicitly provide expertise on topics such as interface design, design process, and tool validation.

Cognitive and Perceptual Psychologists

In the visualization community, interest is increasing in the design and implementation of studies evaluating visualization tools' efficacy. This trend is consequently spilling into collaborative teams. So, you'll often see experts in cognition and perception working with visualization experts to evaluate visualization prototypes and systems.

Data Analysis Experts

Analysis tools that combine computational and visual analysis are now commonly being used in data-intensive domains. The visualization community's increased use of techniques from probability and statistics, numerical and computational mathematics, and signal and image processing has stimulated scientific exchanges between visualization experts and experts in these fields.

Database and Data Management Experts

The growing volume of data available in the sciences and other disciplines precipitates the need to collaborate with experts who focus on managing large datasets. Core visualization expertise focuses on concisely representing data. So, the need is growing (and will continue to grow) for functionality that lets researchers bridge from large, complex datasets to concise, visual representations through advances in databases, data mining, and data organization.

High-Performance and High-Throughput Computing Experts

To keep pace with the growing volume of data and with domain experts' increasing need for tool interactivity, visualization systems must harness modern computing power by using a combination of distributed and massively multithreaded processing. Interactions with experts in high-performance and high-throughput computing will continue as both domain experts and data management experts exploit advances in these areas.

The Revised Roles

By recognizing some of the basic roles that collaborative teams would need to fill, McCormick and his colleagues conceived a basic collaborative structure that still holds. However, they couldn't have predicted the breadth and depth of visualization research over the past 25 years, and how this growth has evolved the basic visualization collaborative team. Our refinement and expansion of the roles reflects the increasing need for visualization as data analysis plays an increasingly vital role in our lives.

Observations, Pitfalls, and Recommendations

In light of our image of modern visualization collaborative teams, we now provide five basic guidelines on how to maintain these collaborations' strength and viability.

Be Multilingual

Much of our disciplinary training focuses on learning terminology, nomenclature, and how to structure ideas. We also learn the concepts, abstractions, and tools of our trade. The result of this is evident in how we communicate with colleagues in our own fields: how we present ideas and make arguments, the vocabulary we adopt for our techniques and methods, and even how we use common words and phrases. Fundamentally, the language of our discipline reflects how we solve problems and taxonomize the world around us. In the linguistics community, one perspective is that words and language affect, and reflect, how we approach and think about problems (this is called the Sapir-Whorf hypothesis or linguistic relativity[8]).

A common instinct when initiating a collaboration with someone from another discipline is to seek a common language. We argue instead that there's great value in understanding your collaborator's language or, as Louise Bracken and Elizabeth Oughton argued, seeking a common understanding.[9] Becoming well versed in your collaborator's language lets you augment your own worldview and problem-solving skills with a new, different approach. This can lead to new insights and perspectives on a problem. From a visualization viewpoint, this knowledge also supports creating intuitive tools that capture the collaborators' mental models.

Although becoming multilingual is challenging and often requires significant time and effort, seeking a common language instead can result in two collaboration pitfalls. First, a common language is unlikely as rich or well-thought-out as the languages of each discipline, limiting the expressiveness of the communication and understanding between the researchers. Second, a dominant personality on a collaborative team can heavily influence the common language and push it toward a single disciplinary language. Instead, by committing to learning each other's language up front, researchers make an inherent commitment to equal partnership and respect. This leads to our next two guidelines.

View Disciplines as Different but Equal

Experts in different disciplines tend to have different worldviews and problem-solving strategies, as well as different perspectives on what aspects of a problem are the most compelling. By acknowledging and embracing these differences, collaborators employ a broader set of strategies, which leads to a richer set of observations.

Another pitfall in collaborative research is to either explicitly or tacitly value your discipline's outlook and goals more highly than your collaborators'. Examples of this would be to view your area of study as more precise, more quantitative, or even less boring. The reality is that we see our own research and way of doing it as the best, most exciting way because we chose to do it. By recognizing this tendency and instead being open to other approaches as equally valid, useful, and exciting, collaborations can lead to a broadening of the individual researchers' skills and techniques and could broaden the individual disciplines.

In a collaboration of equal partnership, the implicit expectation is that researchers on both sides of the project are experts in their respective fields.

Seek Equal Partnerships

We've found that an equal partnership between researchers is a key ingredient for success and for an enjoyable experience. Equality in a collaboration means not only becoming multilingual and respecting different approaches but also ensuring that the collaboration tackles interesting problems for both researchers.

A common challenge in the visualization community is to determine whether a potential collaborative project requires interesting visualization research, as opposed to straightforward software engineering or even just a pointer to existing tools. A pitfall is to not determine this soon enough, potentially wasting significant time and resources. Michael Sedlmair and his colleagues addressed this pitfall as part of a nine-stage design study framework.[10] They discussed several specific considerations for determining a fruitful visualization collaboration early on.

Ensure You're an Expert in Your Field

When a collaboration starts, the flood of new ideas, perspectives, and insights stimulates scientific energy and enquiry. This early excitement is further enhanced by the opportunity to work with an expert in another domain and to learn about and be involved with cutting-edge research in a different field. In a collaboration of equal partnership, the implicit expectation is that researchers on both sides of the project are experts in their respective fields and will remain so throughout the collaboration.

The excitement of learning a new discipline's language and nuances can lead to the pitfall of neglecting to stay current in your own field. Being an expert

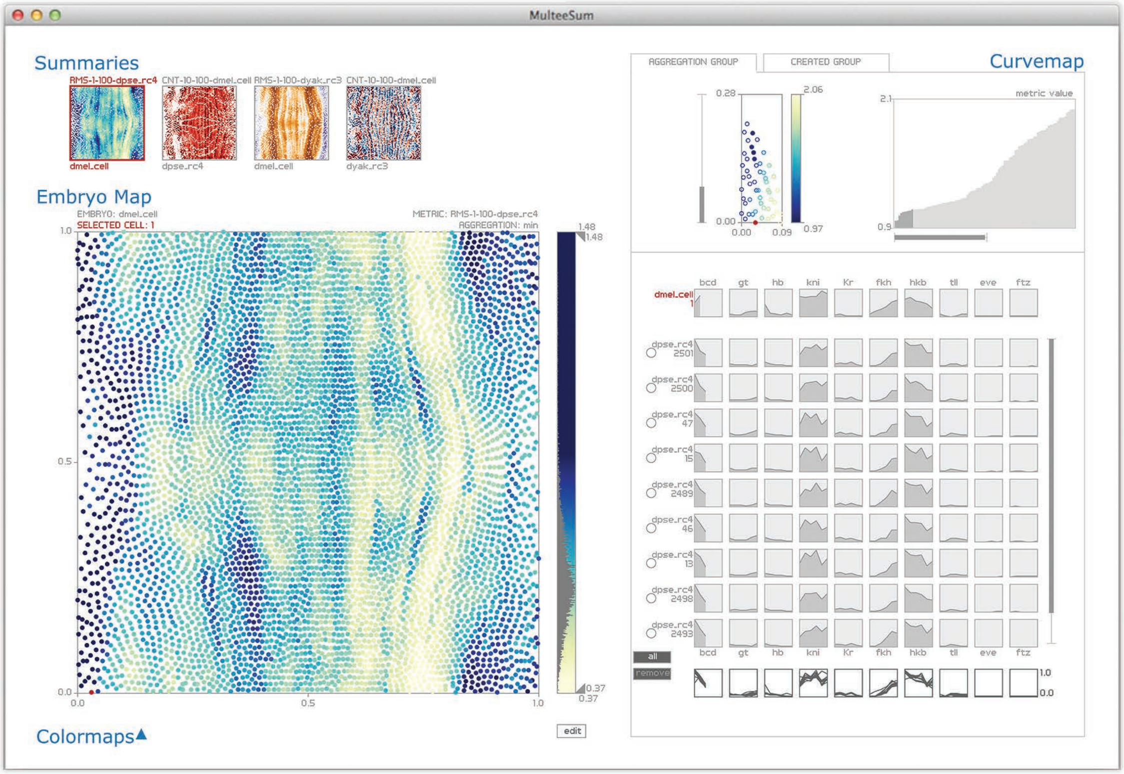

Figure 2. MulteeSum lets users compare spatial and temporal gene expression datasets.[11] Its design resulted from a two-year interdependent, multidisciplinary collaboration between a visualization researcher and a group of systems biologists.

requires remaining engaged and informed about your own field and knowing your limitations. As we mentioned before, becoming multilingual takes additional time and energy—be judicious, realistic, and thoughtful about how you spend your (finite) research resources. Ensure you remain expert in your own field.

Understand Where Your Collaboration Fits on the Spectrum

The number of bidirectional interactions can vary greatly throughout a collaboration—from just two interactions to many frequent ones. Figures 1b and 1c show examples of these two collaboration modes.

These two modes define a spectrum. On one end are independent collaborations that allow the researchers' individual success. If one researcher's project fails, the other's project could continue. These collaborations usually involve a limited number of interactions. On the other end of the spectrum are interdependent collaborations that require both researchers' success to achieve a common goal. These collaborations typically involve frequent interactions throughout the project. A collaboration can be characterized along this spectrum by the number of bidirectional interactions. The more that occur, the more interdependent the collaboration is.

It's important to understand where a collaboration lies on this spectrum to manage the project's risk-versus-gain potential. Interdependent collaborations are much riskier. Your success as a visualization researcher is tightly intertwined with your collaborator's success—if one of you fails, the project is doomed for all involved. This risk, however, is offset by a potentially large gain. Interdependent projects tend to strive for high-impact goals that individual researchers couldn't reach. Such goals rely on complex combinations of skills and methods from multiple fields.

A pitfall is to not be aware of how interdependent a collaboration is. This could result in significant work being wasted if your collaborator doesn't also succeed. Don't let yourself be caught by surprise!

A Case Study

One of our successful collaborations was a project involving a visualization researcher (Miriah Meyer) and a group of systems biologists at the Harvard Medical School. The collaboration began with an introduction from a mutual colleague and spanned two years. During that time, the visualization researcher spent one day a week in the biologists' lab and periodically attended the group's meetings. She assessed information about the group's visualization needs through observation, semistructured interviews, and emails.

This example demonstrates an interdependent, multidisciplinary collaboration—the end result of which neither the visualization researcher nor biologists could have achieved individually. The biological application provided the inspiration and motivation for the design of the MulteeSum visualization tool (see Figure 2). The visualization design process and tool provided a novel framework that led to numerous biological insights and discoveries. The concluding contributions consisted of visualization[11] and biological[12] publications of which the team members were coauthors.

To learn about the group's scientific problem and data analysis needs, the visualization researcher embedded herself in the lab. By working alongside the biologists and attending their meetings, she learned about their language and approach to problems. In turn, the biologists were eager to learn about visualization—they frequently sought out advice on visualization techniques and asked the visualization researcher to give several presentations about the field as a whole. Mutual respect within the collaboration let the individual team members contribute to the project equally and uniquely and broaden their own knowledge base.

Through a series of prototypes, the team articulated and refined MulteeSum's design requirements. By creating an abstraction of the data and tasks, the visualization researcher pushed the biologists toward a much more flexible and extensible system than they originally imagined. This extensibility ultimately let the biologists use MulteeSum to ask varied questions of their data that were never articulated during the design process. In turn, feedback gathered after deploying MulteeSum to the biologists provided a rich set of usage data to the visualization researcher. This data inspired several extensions of the tool related to provenance, interaction, and user control. These extensions were also useful in subsequent visualization projects with other domain experts.

What We Can Now Say

We agree with McCormick and his colleagues' statement that "significant efforts by interdisciplinary teams will produce effective visualization tools." Such teams have also helped bring forth substantial scientific and engineering innovations in many disciplines. Furthermore, McCormick and his colleagues' description of the team members provided a template for what exists today. What they didn't say explicitly, however, but can now be said after over 25 years of scientific exchanges and collaborations, are the following two points.

The Visualization Research Community

First, visualization research now has an intellectual community—a disciplinary home, so to speak. Visualization experts should venture beyond the comfort zone of that community and engage in collaborative exchanges.

Because of the visualization community's applied nature, it will be judged by not only its raw, scientific research contributions but also its impact when it participates in various interdisciplinary and multidisciplinary teams. Visualization researchers offer something unique to collaborative teams, both in how to think about and structure solutions to data analysis problems and in developing intuitive tools for understanding complex data. By engaging with these teams, as *NIH/NSF Visualization Research Challenges* recommended,[13] visualization experts will not only continue to strengthen the field of visualization but can also help move science and engineering forward in general.

When Collaboration Isn't the Answer

Second, collaborative research isn't for everyone.

Given the observations, pitfalls, and recommendations we presented here, some visualization researchers might decide they're not well suited for interdisciplinary or multidisciplinary collaborative research owing to time constraints, research interests, or workplace organization. Explicitly making this decision helps alleviate frustration when expectations aren't met or collaborations fail to materialize or fall apart. Although interdisciplinary and multidisciplinary research can provide many benefits, this doesn't mean that discipline-centric approaches aren't beneficial. The visualization community needs both research styles to maintain its vitality, broaden its intellectual borders, and make an impact.

Collaborative research can be fun, exciting, risky, novel, challenging, and exhausting—all rolled up into one big adventure. At the same time, collaboration has its responsibilities, as we just discussed. Although it's not for everyone, we believe it's a rewarding way to support disciplinary interests while learning, and possibly contributing to, other areas of science and engineering—and beyond.

We'll continue to seek out fruitful, collaborative visualization projects with an eye toward those that push us not only as visualization researchers but also as collaborators. We plan to conduct more detailed and thorough analyses of how successful collaborations function, why they're successful, and what distinguishes collaborative visualization research from collaborative research in other disciplines. We hope this article encourages and informs new visualization researchers as they consider building collaborative relationships. We also hope it stimulates seasoned researchers to contemplate, analyze, and document for the community the components of their successful collaborations.

Acknowledgments

Each of the many collaborators with whom we've worked has in some way contributed to the insights reported in this article. We also acknowledge the academic mentoring and support of Chris Johnson, the director of the University of Utah's Scientific Computing and Imaging Institute. Chris has repeatedly demonstrated many of the traits highlighted here as necessary for good collaboration and has helped us at various stages of our careers. US National Science Foundation grants IIS-0914564 and IIS-1212806 partly funded this research.

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