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Recurrent Collaboration Foster Non-Local Transition of Research Interest

Evidence from the Computer Science Domain

By

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Abstract

This thesis investigates the development of research interests in the field of computer science by examining how researchers transition between research objects and how different collaborative relationships impact these transitions. The study begins with an exploration of the dual spheres of research activities: the idea sphere and the engineering sphere, along with the two primary epistemic faculties—intuition and agency—that enable researchers to navigate between them. Drawing on qualitative data from interviews and case studies, the thesis highlights how these faculties contribute to the generation and evolution of research interests. A case study of a computer scientist's publication trajectory illustrates the difference between local and non-local research interest transitions, showing how researcher's shifts in research objects, accompanied by the reconstruction of epistemic faculties, mark significant changes in research interest.

The quantitative analysis further investigate the relationship between collaborative relationships and local and non-local interest transition. The study uses bibliometric data from the DBLP-D3 dataset and employs measures such as the Distance of Object Engagement (DOE) and the Distance of Community Affiliation (DCA). The findings reveal that while one-time collaborations contribute to incremental changes in research interest, recurrent collaborations play a pivotal role in facilitating non-local transitions that require substantial knowledge and skill adjustments. This suggests that stable, intensive collaborators provide essential support, allowing researchers to adapt their intuition and agency when exploring new, unfamiliar research domains.

Keywords: Sociology of Knowledge; Research Interest; Epistemic Object; Collaboration; Computer Science

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1 Introduction and Literature Review

Understanding scientists' development of research interest is of critical importance because it reveals the underlying factors that drive innovation, shape scientific inquiry, and influence career trajectories. By studying how researchers identify and pursue specific research questions, we can gain insights into the dynamics of knowledge production, collaboration, and adaptation to new technologies or methods. This understanding also helps institutions design better support systems for fostering creativity and interdisciplinary work, while enabling a deeper comprehension of how scientific fields evolve and address emerging challenges.

Given its importance, this issue has long been a central topic of discussion in the sociology of science. Many scholars view the selection and determination of research interests as a key component of their strategic behavior. Kuhn's paradigm theory(1963) explores the stages of paradigm establishment, where researchers' interests are largely shaped by the overall structure of scientific knowledge and its historical shifts . During the 'normal science' phase, researchers primarily focus on puzzle solving within the paradigm, whereas in times of paradigm crisis and establishment, researchers may shift their focus toward more fundamental questions, challenging the established framework and contributing to the formation of new scientific directions. Merton (1973), on the other hand, explains the formation of scientific interest from the perspective of the competition for priority and the accumulation of the Matthew effect. In their pursuit of recognition, prestige, and academic status, scientists often select research directions with potential for breakthroughs. At the same time, Merton acknowledges the influence of curiosity and personal satisfaction on scientists' research interests. Bourdieu (1975) explains the development of research interests through field theory, arguing that scientists determine their research directions by competing for scientific credit or symbolic capital within a competitive scientific field. The formation of research interests is closely tied to a scientist's position in the field, as the accumulation of academic capital guides them toward research areas that can elevate their status. Additionally, the size of the field influences whether researchers' interests converge or diverge.

Although these theories largely explain the development of researchers' interests, they mainly focus on the subjective and strategic aspects of interest formation while, to some extent, overlooking the subconscious and unconscious dimensions. Knorr Cetina (1982) argues that scientific research activities cannot be equated with market activities composed of production and consumption, as the outcomes of scholarly activities are socially accomplished in context and interactively negotiated rather than individually calculated. Thus, although researchers often display the traits of strategic actors in their self-reports and conversations, how well such models explain individual cases remains debatable. Different fields exhibit entirely distinct epistemic cultures, where each culture's unique norms, values, and epistemic objects influence the formation of interests (Knorr-Cetina, 1999). Furthermore, in Objectual Practice (2000), she emphasizes that the uncertainty, incompleteness, and continual unfolding attributes of epistemic objects plays a crucial role in researchers' formation of interest. Researchers' subconscious or even unconscious drives to explore and delve deeper into these objects are a significant source of their research interests.

In this project, I specifically focus on the connection between researchers and the epistemic objects they research, paying attention to their research interests as reflected through objectual engagement.

The availability of large datasets that document research activities offers a unique chance to study the dynamic patterns of scientific production and rewards through advanced mathematical and computational methods (Clauset et al., 2017; Fortunato et al., 2018; D. Wang et al., 2013). One central area of focus is the development of research interests, often explored by examining how scientists switch between different research topics over time. For instance, Foster et al. (2013) applies Bourdieu's field theory to classify the research strategies that scientists adopt as conservative production and risky innovation, as well as their respective rewards. With the development of language models, they have been used to precisely detect scientists' research fields(Rosen-Zvi et al., 2004; C. Wang et al., 2008) and to measure epistemic mobility on the "landscape" of knowledge (F. Liu et al., 2023; S. Zhang et al., 2023). These descriptive models allow for more precise tracking of researchers' interest patterns, such as tracing hotspots or identifying emerging opportunities (F. Liu et al., 2023).

According to the current findings, a variety of factors, both personal and professional, influence a scientist's choice of research problems. These factors range from age (Jones & Weinberg, 2011) and gender (West et al., 2012) to training and mentorship (Malmgren et al., 2010), team influence (Guimerà et al., 2005; Hoonlor et al., 2013; Jones et al., 2008), even serendipity (McNally et al., 2011) and scientist's attitudes and abilities (Azoulay et al., 2009; Bergstrom et al., 2016). In one representative study, Jia et al.(2017) used a stochastic random walk model to accurately simulate the topical span between a scientist's early and late career. These researchers suggest certain regularities and normative patterns in interest development and topic switching, which are worth further investigating.

One particularly noteworthy factor is the collaborative relationship. Coauthors often introduce researchers to new tools, methods, and theories, even when these are not directly applied to the team's specific project. The connection between knowledge diffusion and collaboration has been recognized and studied for a while. For example, it has been observed that knowledge tends to flow more frequently between scholars who have collaborated before (J. Singh, 2005) and those who are closely linked in networks (Sorenson et al., 2002).

Notably, once researchers discover new topics, they may choose to pursue them in the future. Shifts in research interests have become more common over time (Zeng et al., 2018) and have recently been examined (Zeng et al., 2022). These shifts can sometimes be driven by coauthors through a process of social contagion (Ghasemiesfeh et al., 2013), where scholar a, who explores a new topic, influences scholar b to adopt it. As a result, epidemic models have been employed to describe how ideas spread (Goffman, 1966; Goffman & Newill, 1964). In such models, an individual a exposes another individual b to an "infection"—in this case, a new idea or topic—which b may adopt and then further propagate. On a larger scale, the dynamics within collaboration networks, including topic changes, shape the evolution of academic fields (Zhou et al., 2006).

Although these studies have made significant contributions in both theory and methodology of science study, I still see two main limitations in existing research. First, since most studies rely on the meta-information of published papers, we can access their keyword labeling, citation data, field classification codes, or even text-embeddings vectors. However, it remains difficult to understand the dialectical, combinatory, deepening, or comparative relationships between these topic codes or document clusters. As a result, we cannot fully grasp how the topics we identify constitute a researcher's interests. Therefore, the measurement of research interest transitions often stays at a metaphorical level and cannot be further explored (C. K. Singh et al., 2023). Another possible limitation is the insufficient focus on the research process itself. despite the researchers' rich gains in understanding the cost-reward balance and innovative values that accompany scientists' topic-switching, less attention has been paid to the regulatory or normative condition that enables scientists to go through the interest-transition progress. It is difficult to address how researchers acquire the knowledge and skills needed to switch topics, how they identify valuable questions in new fields, or how they balance self-satisfaction with maximizing external benefits.

To be candid, this project cannot fully address the above limitations solely through computational methods. Therefore, by integrating qualitative research with quantitative analysis, I hope to partially address the gaps in existing studies. Due to the difference in cultures between fields, and to ensure consistency in research culture and practice, I focus here solely on the development of research interest in the field of computer science. By analyzing interview materials, I aim to explain two key epistemic faculties that researchers use to construct their research interests. Through quantitative analysis of publication databases and case studies, I aim to further explore how different types of collaborative relationships influence researchers' interest transitions and how these are reflected in specific papers. This may provide insights for further developing qualitative or quantitative research schemes.

With the rapid advancement of computer science, its essential role in addressing social challenges has become increasingly evident (A. K. Singh et al., 2023; Taheri & Aliakbary, 2022). Computer science applications in areas like education, finance, healthcare, and urban management play a key role in supporting the balanced development of the economy, society, and the environment (Harikandeh et al., 2023). Given its profound societal impact and widespread use, computer science has emerged as one of the most dynamic research fields in recent decades (Liang et al., 2023). Therefore, studying research activities in computer science and understanding its epistemic culture is a meaningful endeavor in itself.

2 Research Activities in Computer Science

This thesis consists of three progressively in-depth sections: interview analysis, case analysis, and quantitative analysis. Before delving into the quantitative and qualitative analysis of the relationship between research interest and collaborative relationships, I would first like to provide a detailed explanation and interpretation of research activities in the field of computer science, drawing from interview records from Youtube[1]. By analyzing the background and progression of researchers' projects, along with the formation and transformation of their research interests, we gain insights into what actually occurs during their transition in interest. This analysis helps identify the key conditions, considerations, and events involved in these transitions, enabling us to establish a more effective analytical scheme tailored to the epistemic culture of the computer science field.

2.1 Two Spheres: Idea and Engineering

The following is a researcher's description of his research trajectory over the past year during an interview. This type of process is quite representative among researchers:

> I joined [the interpretability group] when we were five people. There were so many ideas floating around, and we just needed to really execute on them, have quick feedback loops, and conduct careful experimentation. That led to signs of life and has now allowed us to scale significantly. And I think that's kind of been my biggest value add to the team, which is not all engineering, but quite a lot of it has been (Bricken et al., 2024).

When further asked whether his research process was mainly engineering work, he clarified:

> There's why it's not all engineering, because it's about running different experiments, having a hunch about why something might not be working, and then

[1] All interview materials in this paper are sourced from YouTube. For details about the interviewer, interviewee, publication date, and interview topic of the videos, please refer to the appendix VI. The versions used in this study correspond to the same time as the completion of this paper

> opening up the model or weights to see what it's learning. Okay, well, let me try and do this instead. A lot of it has just been being able to do very careful, thorough, but quick investigations of different ideas (Bricken et al., 2024).

This interviewee's projects mainly focused on computational neural science and was primarily focused on the topic of "sparse encoding", which allows for more efficient data representation and processing. Many researchers may not describe their research experience using terms like 'quick' or 'thorough' with the same enthusiasm as him, who was just beginning his scientific career. Still, most would agree with breaking down their work from the perspectives of "idea" and "engineering". For the projects researchers are working on, the abstraction and articulation of their ideas, along with implementing their projects in a valid and reproducible way, are both crucial to the project's completion and success.

Let me further clarify and extend the distinction between the idea perspective and the engineering perspective. When researchers talk about their work, the descriptive language and evaluation frameworks they use from the idea perspective and the engineering perspective are completely different, even though they are referring to the same actual progress and project. Let me continue by using another excerpt from the same interview to illustrate this point. When the interviewee discussed the process of research over the past year and a half, he provided a more detailed description of his projects' engineering implementation as below:

> I feel like I have been very lucky, the timing of different progressions has been really good in terms of advancing to the next level of growth . . . [During this project] I don't get blocked very often. If I'm trying to write some code and something isn't working, even if it is in another part of the code base, I will just go in and fix that thing or at least hack it together to be able to get results. And I've seen other people where they're just like 'help!' I don't think it's the excuse for them not to go all the way down (Bricken et al., 2024).

At the same time, when he was asked during the conversation to describe how these projects contribute to the community at idea level, he said the following:

> I got into computational Neuroscience and didn't have much business being there. My first paper was mapping the cerebellum to the attention operation and Transformers. My next work was on sparsity in networks inspired by sparsity in the brain, which was when I met Tristan Hume. Anthropic was doing the "SoLU", the softmax linear output unit work, which was very related (with my works) in quite a few ways. Let's make the activation of neurons across a layer really sparse, and if we do that, then we can get some interpretability of what

> neurons are doing. That started the conversation I shared drafts of that paper with Tristan. He was excited about it, and that was basically what let me become Tristan's resident and then convert to full-time. During that period, I also moved as a visiting researchers to Berkeley and started working with Bruno, and Bruno basically invented sparse encoding back in 1997. My research agenda and the interpretability team seemed to just be running in parallel with just the same research taste (Mishra & Shah, 2024).

Now, when we juxtapose these descriptions, we can gain a comprehensive sense of this interviewee's progress: Over the past year and a half, he entered the field of computational neuroscience, a domain he initially knew little about, and participated in the discussions and projects of the "interpretability group". He conducted several studies mapping neuronal activity patterns (including attention, sparsity, etc.) onto artificial neural network structures. Throughout this process, he established connections with researchers or groups working on similar topics. As the project advanced, he continuously transformed valuable ideas into experiments, solving various engineering problems encountered along the way, and scaled successful projects to larger experiments, ultimately leading to meaningful publications.

However, when we compare scholars' self-reports from the idea perspective versus the engineering perspective regarding their conduct and achievements, we can tell that they are quite different. In the description from the engineering perspective, the interviewee is concerned with how the project (or series of projects) was completed—how he decided on the configuration of an experiment, how he handled the feedback from the results, how he made the model work when the feedback was not ideal (checking the code or hacking it together), and how he scaled up the experiment when the feedback was good ("a good timing"). The engineering perspective prescribes constructive progress: through a series of structured and effective conduct, a virtual, flawed, primitive, toy-like "thing" was made into a real, functioning, mature, and large-scale one.

In contrast, the idea perspective takes a completely different path. Here, he mainly discusses how they drew inspiration from brain structures to improve the attention mechanism in artificial neural networks, which in turn could inspire further improvements or lead to seeking new sources of inspiration. The idea perspective unfolds a signifying process: the researcher conducts a process of breaking down, combining, analogizing, and complementing, to extract a specified and concrete piece of knowledge from a general, unquestionable, and widely accepted understanding or knowledge, which he can personally claim and sign off on. However, the validation and realization of this piece of knowledge is not within the scope of the idea perspective's consideration.

So why is the engineering-idea division so important? Although researchers often talk about being a good coder or developer, and refer to the skill of writing papers as 'story-telling skill,' these may seem like just different levels of abstractions of the same work at different levels. Beyond that, what is the significance of distinguishing between the engineering perspective and the idea perspective? This distinction is crucial for understanding researchers' decisions and choices, and their development of research interest. As mentioned earlier, the meaning of research results is socially accomplished-in-context and interactively negotiated. During the research process, scientists often do not know exactly what is expected or what can be fulfilled by their endeavour. In this context, the engineering perspective and the idea perspective correspond to key sources through which scholars perceive, judge, and generate research interest.

When asked how one can find or decide challenges to work that have some importance or impact, a research scientist at Google systematically outlined the methods:"

> . . . There are three challenges: first of all, doing the basics. I think there are no problems here, doing some courses and reading some textbooks, but that's the knowledge helpful three years back, not now. Second is reading the right paper, and there you need guidance. Twitter helps, you know, if you follow some of the high-profile people. From their thoughts and papers, we can get some insight. But even then, it's incomplete. [In the] last few years, many of the critical stuff [has not been published]. Many of the papers have now turned into tech-reports, and many details are missing [in these reports]. That's where the challenges come from, like how do you know the reality, or how real things work. And there I would like to say, meeting people, trying to go for internship, or working with industry for some time. That's where the real skill and real knowledge can come from. And once you know that, you can do what you want to do. Like they said, unless you make your hand dirty, you don't learn. You have to be in the space to learn and to really know what to do next (Mishra & Shah, 2024).

This researcher's responses consistently revolve around the question of 'how to figure out what to do next,' and his opinion is both common and representative among researchers (Interviewees & Shah, 2021). Researchers gather information from courses, journals, conferences, and social media with varying levels of up-to-date knowledge, using it to assess what people are currently focused on. This is information at the idea level, but it does not reflect how things actually work. The necessary condition for understanding reality is to 'get your hands dirty'—to engage in actual research work and accumulate engineering experience. Through this engineering experience, researchers learn about the challenges behind these issues and which areas of focus can realistically be addressed.

In summary, research scientists work with two different perspectives: the engineering one marks objects within reach, which consists of the researcher's own engineering experience and expands as they accumulate experiments conducted. Although its scope is limited, it has the highest degree of reality. I borrowed from Alfred Schultz the concept of 'manifold strata of consciousness' (Schutz, 1962) to explain the configuration of this perspective. Schultz used the concept of 'manifold strata of consciousness' to explain the structure of people's experiences when engaging with the world. Individuals develop different attitudes or perspectives depending on their form of interaction with objects in different strata. Two key strata are the 'strata of attainable reach' and the 'strata of attainable reach by fellow mans (potentially attainable reach).' The engineering perspective aligns with the 'strata of attainable reach' as their engineering experience is composed of reachable objects and their interactive experiences with these objects. In the meantime, a conscientious researcher can always reproduce their own papers and conduct the experiments they have previously carried out. Their articles, therefore, act as signifiers pointing to objects that have been realized in the past and can be realized again when needed.

On the other hand, the idea perspective is oriented to the 'potentially attainable strata'. The objects from idea perspective are within researchers' potentially attainable reach. Researchers gather information from articles, social media, or conferences to construct this sphere, based on objects that others claim to have realized. This information may contain engineering details. However, all the information from github, paper, news, or social medias are only second-hand, thus partial experience. Unless researchers carry out the 'dirty work' themselves to realize these objects, their attainability remains incomplete or partial. Thus, researchers immersed solely in the idea sphere can never exactly 'know what to do next.' Objects within the idea sphere lack the same sense of reality as those in the engineering sphere but reflect the current focus of insiders and outsiders in the field, as well as which unsolved problems may have the greatest impact.

From this point forward, I will refer to these two strata of experience in research activity as the 'engineering sphere' and the 'idea sphere.' These spheres are not isolated from one another. They first overlap on concrete objects:research objects can be implemented, operated on, and modified in the engineering sphere, while they can be described, theorized, and hypothesized in the idea sphere. They also overlap in the construction of a researcher's interest. Research, being a constructive and, to a large extent, creative practice, is never in a fully projected or defined state (Knorr-Cetina, 2000). This means that researchers constantly and spontaneously encounter junctions which require them to project future actions. Researchers' interest manifest in these junctions and projection.

According to Schultz, this projection occurs in the future perfect tense, where researchers anticipate the outcome of future actions within both the idea and engineering spheres. By engaging in this anticipated, virtually reflective experience, they determine the meaning of their actions. The generation of this meaning depends on the interaction of both perspectives and is oriented to their research interest. To clarify potential ambiguities, while words like 'anticipate' and 'determine' may suggest prediction and measurement in a calculative sense, this process is quite different from predictive or calculatory work. First, researchers cannot anticipate all possible actions within "the space of possibility". Second, the judgment of the meaning is not always something that can be calculated or compared. There is a significant affective component to this process, which will be further discussed in later sections. In the next section, I will elaborate on two epistemic faculties that help researchers consciously, subconsciously, and unconsciously form oriented projections.

2.2 Two Epistemic Faculties: Intuition and Agency

The idea perspective and engineering perspective both stem from the researcher's own or others' project experiences, they differ in the situations in which they are generated, the channels through which they are changed, and the ways in which they exert influence. And scholars combine both perspective to develop their interests. They are not only integrated in researchers' epistemic or decision-making processes but are also combined in many practical situations, such as reproducing papers, interpreting experiments (from perspectives such as physics or mathematics), and more. These actions play a central role in researchers' work. In this section, I will elaborate on intuition and agency, two epistemic faculties for the integration of the two perspectives or spheres. They serve as key standards by which researchers assess both their own value and the value of other researchers.

As articulated by Knorr Cetina (1982), what scholars care in their research decisions is the maintenance and enhancement of their self value, which contains the convertibility of prospective resources into locally relevant 'currencies.' Nevertheless, they are constantly in a state of not knowing exactly what is expected and what can be fulfilled. A common approach to navigating this uncertainty is to 'see what others are doing.' According to the quotes below, to "back and forth" between ideas and practices.

> Organically, this is often like the way things turn out to be... In terms of exploration, maybe you wanted to be doing some combination of spending time learning about certain papers or techniques that you start off being excited about and then at the same time, you're trying to work on concrete projects to really dive into the details of trying to do research there. These two things are beating off of each other. Like, when you first start reading papers, it's illuminating and it's interesting, but the depth in which you understand them is different once you've started doing research yourself in that area, because you better understand what are the important parts, what are the less important

> parts, what you are interested by and what's less exciting to you. So you like kind of back and forth between these (Raghu & Shah, 2021).

This interview provides a clear example of how researchers develop an understanding of something ('in depth') by combining the idea sphere and the engineering sphere, and how this understanding leads to identifying the 'important and less important parts' of the problem. This understanding gradually matures into a broader comprehension of the people or community working on this subject. In one of the interviewee's blog posts, she elaborated: "The problems that we aim to tackle are incredibly difficult, and progress relies on the cycle of you building off of others' ideas and others building off of your ideas. This is a crucial factor to keep in mind when exploring research directions. What is the community excited about, and why? Are there shortcomings or gaps? Are there natural next steps to study? (Raghu, 2020)" In this process, researchers start with an acquired idea ('certain papers or techniques that you start off being excited about') and reconstruct their understanding of the idea through engineering experience (from 'illuminating' to 'back and forth' and finally to 'cycles of building off of each others' ideas'). Ultimately, they gain insight into the relevant system of local currencies, which includes current focuses, shortcuts, gaps, and so on. These elements assemble the scheme of "local value" that researchers refer to when making research decisions.

Here, I use an excerpt from another interview to illustrate how a research decision is made based on this kind of intuition.

> I have been very good at picking extremely high leverage problems, [which are] problems that haven't been particularly well solved so far, perhaps as a result of frustrating structural factors. As you mentioned before, they're like we can't do X 'cause this team won't do Y, and ... Well, I'm just going to vertically solve the entire thing [laughter] (Bricken et al., 2024).

This paragraph more clearly demonstrates the 'back and forth' process where engineering and community knowledge complement the idea perspective when a researcher encounters an unresolved problem. By combining their understanding of the engineering challenges involved and their knowledge of the situation in other groups, they conclude that the problem remains unaddressed due to visible obstacles, rather than because solving it lacks value. Other parts of the interview also reveal that this researcher is adept at leveraging his comparative advantages to tackle high-leverage questions that have yet to be solved.

In summary, when a researcher encounters an idea relevant to them, they do not merely assess it conceptually. According to Schultz, people's experiences from the 'strata within attainable reach,' their practical experiences, form the basis for the criteria and standards they use to assess and infer the objects they encounter. Thus, researchers draw on their engineering experience and skill-sets, whether closely or loosely connected to the idea, to reconstruct it and estimate the potential significance of realizing it. This is how a researcher's interest is "tuned". The transformation from idea to interest relies on intuition formed from past engineering experience. The term 'intuition' is used here not only because it frequently appears in various interviews, but also because it often involves highly personal, difficult-to-analyze or express feelings. It represents the affectional dimension in a researcher's decision. For example, in the interview, the researcher expressed that intuition, to some degree, can only be felt but not prevised:

> You get good ideas exactly when you want to sit on the beach and not think about research, at least for me... There is no cookie-cutter recipe for good versus bad ideas. Typically, if there is such a recipe, that essentially means it's more structured by someone else. And the whole point is that you are structuring... I can't define any of them. I can only tell you whether one is something. If you present one, I can tell you whether it's good or bad (Kambhampati & Shah, 2022).

This is part of the professor's answer on what forms a good PhD project in terms of finding a good idea. Here, we can see the notion he uses, "structuring", resonate with the previous argument of using engineering and other experience to further form the idea. It is important to clarify that, although the researcher repeatedly emphasized in the interview that forming intuition requires active experimentation, the faculty of intuition is passive: a response to external stimulation. When a researcher senses external interest as signified by ideas, they use intuition to decide whether to amplify or downscale that interest into their own personal interest.

In contrast to intuition, researchers have another way of generating interest—an active, affectional process where they use their agency to illustrate an idea through manifold (and mainly engineering) endeavors. Take another excerpt from the interview above:

> I start thinking people have become research sentient when they can defend an idea. They almost take it personally when you are talking about the downside upside of their idea. When you start feeling that, then you at least start becoming a researcher. Not every researcher will be having impact and, you know, they say that what is luck is opportunity meeting preparation (Kambhampati & Shah, 2022).

As illustrated by the interviewee worked on sparsity encoding, the engineering endeavor (software engineering in his case) is crucial. Countless issues needed to be overcome through coding, debugging, checking the resources, maintaning the datasets, etc. Beyond the engineering skills and techniques, the agency researchers speak of also emphasizes a kind of engagement and commitment—a proactive adjustment based on possibilities in order to respond to and leverage uncertainty. As mentioned in the interview above, 'luck is when preparation meets opportunity. And alone the way, stubbornness is somehow necessary as well:

> And inversely, my own situation is doing these works independently and producing more interesting things. It was my own way of trying to manufacture luck, so to speak, and do something meaningful enough that it got noticed. . . . There's this line: the system is not your friend, and it's not necessarily to say I'm actively against you or it's your sworn enemy. It's just not looking out for you. I think that's where a lot of the proactiveness comes in, like there are no adults in the room, and you have to come to some decision for what you want your life to look like and execute on it. Hopefully you can then update later if you are too headstrong in the wrong way, but I think you almost have to just kind of charge at certain things to get much of anything done, not be swept up in the tide of whatever the expectations are (Bricken et al., 2024).

The interviewee working in the field of sparsity coding further explained his views on risk and uncertainty in research. In this context, the agency represents the act of anchoring oneself to a particular position and maintaining that stance. This agency reflects a tendency, to some extent, opposite to intuition—namely, the degree to which one remains unaffected by external expectations or trends. This highlights the affectional aspect of research decision-making. Because both the demand and the solution are uncertain, scholars emphasize agency alongside meeting visible external demands. Some researchers even believe that focusing too much on perceived trends can be harmful.

> Reading less is important if you want to do great in research. It's a human tendency if you read more, you get biased, right? If you meet someone who tells you some words, you might say the same words the next day. It just biases our behavior. Learning from a specific person, specific textbook, or specific paper biases you with the author or the narrator's observation in their perspective of things, which is worked. That's why we learn, but it may not be the best way, right? You know, like LSTMs were successful, but Transformers came. Some people make that mistake which is spending couple of hours everyday to read. I don't recommend that because if you read five papers each day and I ask you a question, everything you answer is a composition, if not directly from them.

> That's harmful. It can give you one paper and you can go to the conference and get some citations, but that is not going to create a breakthrough and is not going to make your name (Mishra & Shah, 2024).

The interviewee expressed that manifesting agency sometimes requires avoiding "reading too much", as well as the interference of intuition during the reading process, in order to maintain independence. The absorption and processing of ideas through intuition is largely subconscious and semi-automated, and the same applies to agency. Researchers are aware of this, which is why they "tune" their subconscious activities to align either with their observed scheme of meaning or with the position they stand for.

In summary, researchers' intuition and agency help them combine the idea and engineering spheres. These two epistemic faculties allow them to develop research interests with certainty. Intuition drives researchers to reconstruct the ideas they receive and the interests they sense. It transforms these into their own interests, helping them effectively 'respond' to external stimuli. In contrast, agency pushes researchers to realize and manifest ideas through engineering and other work. It expresses their personal stance as a personalized interest, while also shielding them, to some extent, from external influences. These factors help researchers navigate the uncertainty of 'not quite sure about what is expected and what they can offer.' As a result, their research interests carry both epistemic and affectional impacts on the relevant ones. Intuition and agency are central to how researchers assess their own value. Well-developed intuition and agency are also marks of a mature researcher. Additionally, they reflect the affectional or libidinal aspects of decision-making progress at both individual and collective levels.

2.3 Collaborative Effort

Intuition and agency is not only play essential in researchers' self-assessment, but also play a key role assessing their collaborative relationships. People are highly sensitive to differences in intuition and will strive to ensure that they have shared intuition either at the start or during the course of the collaboration. Thus, whether researchers share intuition is an important criterion for initiating a collaborative relationship. Some researchers believe that finding a collaborator with shared intuition is crucial (like for prominent PIs selecting collaborators from many candidates):

> For selecting talent, sometimes you just know. After talking to Ilyad for not very long, he seemed very smart, and then, talking to [him] a bit more, he clearly was very smart and had very good intuitions as well as being good at math, so that was a no-brainer. There's another case where I was at an NIPS conference; we had a poster. Someone came up, and he started asking questions about the

> poster, and every question he asked was a sort of deep insight into what we'd done wrong. And after five minutes, I offered him a postdoc position (Hinton & Hellermark, 2024).

In other cases, researchers often collaborate with people who have different intuitions at starting stage. Researchers tend to believe that establishing shared ones during collaboration is a key factor for a successful relationship, difficult but worthwhile. It is not only beneficial for making good collaborative efforts but also advantageous for the researchers themselves, which in turn influences their future decisions. 'Learning different minds' is a common expression in interviews, referring to the process of gradually learning how others' intuition works during the course of collaboration:

> It takes time to build relationships or to interact with people that have different thought processes or come from different backgrounds, but I think every time you do it, and you invest the effort, it's like you have basically one more way of thinking in your kind of tool belt. I always am and always recommend making decisions at least partly based on the people you are going to work with. . . .It really took a while to find the right vocabulary and the right kind of language, but it was very rewarding once you were on the same page and you could actually work (Stutz & Shah, 2023).

If, in a collaborative relationship, researchers fail to establish shared intuition due to a lack of ability or willingness, the relationship is often regarded as a failure:

> I would also like to complain about [people from] computer science. I know many students who are working in health care. They are super deep into computer science, and they are super deep into models and architectures. Even if they are working in a healthcare domain, they never try to understand that domain. For example, you are taking into account a very complicated problem in the neurologic field, like you want to predict microbleeds. It's a very, very complicated problem, and practically identifying microbleeds from image data [is] something experts cannot identify. You have to understand what is the problem, what kind of data to use, why it fails and how to improve it. . . You have to understand the actual domain before you move to the model development and build more layers and add more parameters (Banerjee & Shah, 2024).

Evaluations of agency often focus on whether the other person has the engineering skills to solve the idea. In Hinton's interview, he mentioned another valuable type of collaborator: those who are excellent at engineering. They can quickly develop code or tackle complex programming tasks (Hinton & Hellermark, 2024).

Now that we understand the epistemic faculties—intuition and agency—that play a crucial role in their decisions, both for developing interest and assessing collaborative relationships. They occasionally need to wrap up their current progress and explore new directions. Researchers expand or change their research directions for various reasons, such as junior researchers frequently shifting focus to explore the landscape and find a good starting point. Scholars also broaden their direction when research projects hit a bottleneck, thereby they need to expand possibilities and split risks. Additionally, major breakthroughs and trends (e.g., LLM) may also drive researchers to shift toward popular directions in order to keep up with the State of the Art ("SotA"). This explorative process impacts both their idea and engineering spheres, as they encounter unfamiliar ideas and face new engineering tasks. Another crucial aspect that cannot be overlooked is the reconstruction or expansion of their epistemic faculty, which involves adjusting their intuition and agency to help them make informed decisions in the new domain.

> I still remember when we started working in the medical field. Whenever I started a new project, I started reading about the domain itself. For example, when I started with the Palmar embolism project with Matt Iren, I spent hours and hours with Matt, and Matt was drawing on the board to explain to me what the problem is was, what is the implication, how it looked in the image. Until you develop that understanding [apart] from computer science, you would never be able to work on any project (Banerjee & Shah, 2024).

As this professor recalled, collaborators from the target direction provide immense help to researchers. To ensure the smooth progress of the project, collaborators are often willing to thoroughly explain the engineering details and critical issues of the target field. This is usually the case where people of different knowledge backgrounds come with a shared and often interdisciplinary interest. In addition to collaborators from different fields, another type of collaboration that can play a crucial role in the exploration is the 'advancing together' relationship. It is not diversity but similarity that is crucial in this case.

> And if you identify an exciting, new research direction of interest to the field, it's often useful to build a community around that direction — this can happen through initiating collaborations, disseminating key open questions, and organizing workshops (Raghu, 2020).

A group of researchers with an intense intellectual connection could be helpful to researchers at any stage, but this is especially important when researchers are marching in a new direction where they *lack* well-tuned intuition and agency.

> I studied robotics as an undergrad ... After reading Gwen's scaling hypothesis post, I got completely scaling-pilled. Clearly, the way you solve robotics is by scaling large multimodal models, and I was trying to work out how to scale that effectively. And James Bradbury who at the time was at google, saw some of my questions online where I was trying to work out how to do this properly. He was like, 'I thought I knew all the people in the world who were asking these questions, who on earth are you?' ... He reached out and said, 'Hey, do you want to have a chat and you want to explore working with us here?' ... And I was hired as I understand it later as an experiment in trying to take someone with extremely high enthusiasm and agency, and pairing them with some of the best engineers that he knew (Bricken et al., 2024).

This excerpt provides a more vivid example of how team-building brings together people who are focused on similar issues. Although such teams may not always result in complementary intuition, they can significantly enhance the researchers' agency. This helps them "communicate efficiently, quickly deploy experiments, and validate ideas," which is highly beneficial for their exploration. Establishing a core-set and allocating the necessary human resources is also a common method many researchers use to catalyze or accelerate specific research. In summary, whether it's a guide in exploring new directions or an explorer advancing together, collaborative relationships help researchers develop better intuition and agency when exploring new directions, facilitating their transitions.

This section's analysis identifies the primary components of research activities (the two spheres), the tension between them, and the epistemic faculties researchers use to balance this tension. Researchers' interests are, in fact, constructed through these two faculties. In the next section, I will delve into the project level of an individual researcher using a representative case study. By focusing on the researcher's engagement with specific objects, I will explore how their interests are constructed and transition over time, and how their epistemic faculties,intuition and agency, are adjusted alone the way.

3 Case Study: Structure of Wanting

3.1 Objectual Wanting

With an understanding of the normative structure of research activities in the field of computer science, we recognize that researchers engage with two interconnected spheres of meaning: the engineering sphere and the idea sphere. While these spheres are tightly linked, researchers approach them with differing attitudes and interact with each in distinct ways. We identified *intuition* and *agency* as the principal epistemic faculties that enable researchers to integrate their experiences from these two spheres and guide their interest. However, up to this point, our discussion of research interest has remained broad, encompassing aspects such as pressing challenges, mechanisms needing explanation, or exploratory combinations and improvements—essentially, epistemic impulses that drive researchers' decisions and future projections.

In this section, I aim to narrow the focus to a more specific type of interest, one that is intimately tied to research objects. This is the form of interest that individuals or research groups particularly wish to explore, develop, or solve, which I refer to as 'wanting,' a term borrowed from Objectual Practice (Knorr-Cetina, 2000). This type of interest stems from the inherent incompleteness of research objects, which continuously generates new questions and possibilities, prompting further investigation and refinement. Such 'objectual interest' is restrictive (S. Zhang et al., 2023), regulatory (Collins, 1981), and even directive (Knorr-Cetina, 2000) in shaping researchers' conduct within their projects. In other words, the influence of objectual interest is both crucial and determinative at the project level. Examining these interests closely not only deepens our understanding of how researchers configure their interest at project level but also provides valuable insights for large-scale quantitative analyses.

In this section, I will use a representative example to illustrate how transitions between research objects signify shifts in research interest. To establish this connection clearly, we must first revisit the concept of the "wanting structure" from Objectual Practice. This structure within a research paper can be identified by examining how authors focus on specific research objects and the questions that evolve around them. Clues can be found in recurring language that emphasizes unresolved challenges, open-ended possibilities, or gaps in current knowledge that the researchers aim to address. The progression of arguments or hypotheses in the paper often reflects a series of exploratory steps and problem-solving efforts, highlighting the researchers' continuous engagement with the object. Additionally, citations and mentions of future work may indicate how the object continues to develop, signaling the researchers' sustained drive to deepen their understanding and pursue further inquiry.

It is worth noting that "objectual wanting" serves as the intersection of researchers' experiences within the engineering sphere and the idea sphere. When engaging with a specific research object, researchers' engineering expertise enables them to interact with and extract value from floating ideas, thereby exercising their agency. On the other hand, researchers' intuition assists in integrating appropriate ideas into their projections or plans for research activities. Therefore, at the object level, we can more clearly observe how researchers' epistemic faculties interact with other spheres and how their interests are generated and transformed accordingly. By analyzing these elements, one can trace the researchers' evolving relationship with the object and the ongoing structure of wanting that drives their inquiry. Additionally, the researchers' engagement with objects particularly reflects the adjustment or reformation of their epistemic faculties, which will be demonstrated in the subsequent case analysis. In the following part, I will address two questions: how the transition of research interest and adjustment of epistemic faculties is reflected through specific objectual engagement, and how we can understand the role of collaboration in this process.

3.2 First Three-year Window and Local Transition

Our analysis begins with exploring a typical structure of objectual wanting. We will investigate how researchers, through a constellation of objects and the indexing of objectual wants—whether fulfilled or left open-ended—direct their projects toward specific research interests. Using researcher G's paper, A multilevel parallel and scalable single-host GPU cluster framework for large-scale geospatial data processing (2014), as an example, this study serves as a clear illustration of how multiple chains of wanting intersect and converge into a coherent research interest.

We can find rich background information on this author's website. The main contributor of this paper began publishing in 2003, and by 2016, he had already published 10 first-author papers. His personal homepage[2] reflects that he is still active in research ('he is currently mentoring or leading . . . '), with his main focus on 'remote sensing and satellite image processing.' He also has membership of several related groups. When we examine his profile on the university website and his IEEE profile, we can clearly observe traces of development within his research domain.

First, there is a focus on high-performance computing. His IEEE profile specifically mentions his PhD affiliation with the Medical and Biological Lab. This is an important clue: due to the similarities in data characteristics and task composition, research on medical images and remote sensing images (though seemingly unrelated) overlaps significantly, with many important remote sensing image techniques derived from medical image technologies. This information indicates that his educational background comes from the traditional core-set of digital image processing.

His second lab affiliation information shows that during phd, he was involved in projects on high-performance computing, database development, and information retrieval within the CGI group. This suggests that another major focus of his research is high-performance computing and information processing. With this information in mind, we look at his description of his own interests:"He is currently mentoring or leading research projects in several areas including data science, machine learning, computer vision, multi-modal analytics, high-performance computing, Internet of Things (IoT), and geospatial analytics. His

[2]Here I take into consideration his personal page in UMissouri and on IEEE

research interests also include knowledge-driven multidimensional indexing, multimodal analytics, computer vision, pattern recognition, computational intelligence, databases (geospatial, media-content, and traditional), parallel/distributed systems and information theory in support of media database systems." We can clearly trace his core research focus on remote sensing images, image algorithms, and high-performance computing. As deep learning advanced, his research expanded to include deep neural network image algorithms. Additionally, he explored how these core objects are related to other fields, such as geographic spatial analysis derived from remote sensing images, multimodal algorithms derived from image algorithms, and media data analysis derived from high-performance computing. We examined the changes that occurred across two adjacent three-year windows. Our analysis is set during a critical period of his object transition, specifically his shift from traditional image algorithms to deep learning algorithms. Knowing from his 2024 profile that he underwent this transition, we will analyze his publications from this period to closely investigate the process and nuances of this shift.

The paper begins by focusing on high-resolution remote sensing images, which represent the most important object for the researcher. 'The variety and scale of geospatial data necessitates the development of general purpose high-performance processing frameworks in order to apply methods of ever-increasing computational complexity to these massive data sets.' From this statement, we can see that the variety and scale of high-resolution remote sensing images create a 'wanting for high throughput processing,' which leads to the second object: the "high-performance computing framework". As mentioned earlier, these refer to two of the most important objects the researcher has focused on throughout their career.

However, the problem of large-scale frameworks has not been well addressed at the algorithm level in existing research: "Many non-trivial (in theory and implementation) state-of-the-art image processing and computer vision algorithms do not scale well to the size of full remote sensing imagery scenes." Therefore, the wanting for the completion of high-performance computing framework shifts to the hardware level: "This has inspired an ever-increasing amount of research into parallel architectures as computing solutions for geospatial data.[3]" This leads to a need of better designed parallel architectures.

The wanting for hardware systems, in turn, unfolds the use of GPU systems as a response: "However, many approaches involve hardware solutions that may be cost-prohibitive for some researchers. A promising, cost-effective solution to geospatial raster data processing is the use of modern GPU hardware and general-purpose GPU (GPGPU) programming." Up to this point, G has mostly described ideas widely recognized within the field, showing

[3]It's important to note the implicit assumption here that researchers often divide computing systems into software and hardware, with software referring to algorithms in this context. Problems should be solved on either side or both.

little in terms of intuition (as studying GPUs was a common intuition at the time due to hardware constraints).

In the next section, the author begins to more explicitly demonstrate their intuition by referring to more subtle and concrete objects: GPU combined with the CUDA API (or OpenGL, etc) can handle remote sensing image processing, but lacks the capability for large-scale data processing. In fields like text processing, GPUs have demonstrated their large-scale processing capabilities through integration with algorithms, but they lack the general-purpose programmability needed for broader applications. Another wanting for the high-performance computing framework is the need for general-purpose programmability, which leads to the introduction of the partition-and-conquer standard using GPU cluster nodes (integrating GPUs into traditional computing clusters).

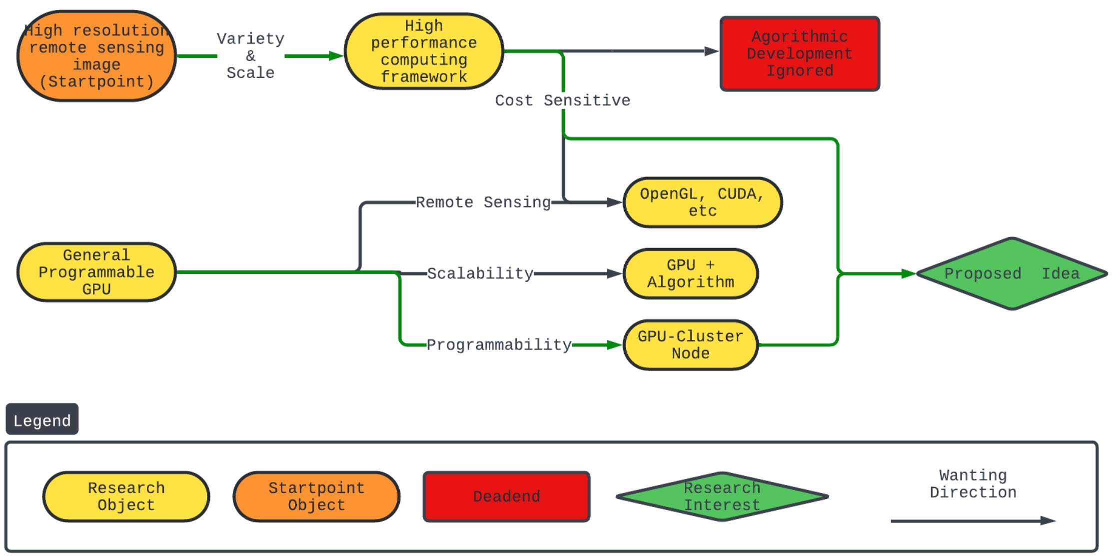

Figure 1: Wanting Structure for Scott, England, et al. (2014)

The network diagram Figure 1 shows how the chain of objectual wanting, as presented by the author, logically leads to the paper's core interest (the solution in this case). The squares represent the objects mentioned, and the lines indicate the wanting associated with each object. The chain of wanting that forms the paper's core interest is highlighted in green, which is signified from the idea sphere and validated in engineering sphere in this paper. Most papers have two or more starting points for these chains, which means they may connect objects that are not directly related previously. For example, in this paper, remote sensing image and algorithms are not inherently linked. Additionally, not every object mentioned will have a direct connection to the final interest (like the two nodes derived from GPU). From this diagram, we can see that the paper's interest is built by extending, merging, and grafting onto previously unfolded wanting connections from earlier research. This results in a chain that is logically coherent in the idea sphere and validated in engineering sphere.

Regardless of whether the idea construction of the paper is innovative or creative, or whether its engineering deployment has flaws or aspects worth further discussion, the interest of this paper represents a curated unfolding of wanting and may be referenced in future work. Based on the current analysis, we can define interest as manifested in a project, more specifically, as the fulfillment of one or more objectual wantings. Each individual work may only provide temporary fulfillment, it retains the potential to continue unfolding in the future. It's also important to note that each object can be both the starting point and the endpoint of wanting. For example, the high-performance computing framework in this paper is both a solution to a problem and the source of subsequent challenges, and this applies to other objects as well. Wanting can loop through objects in various situations.

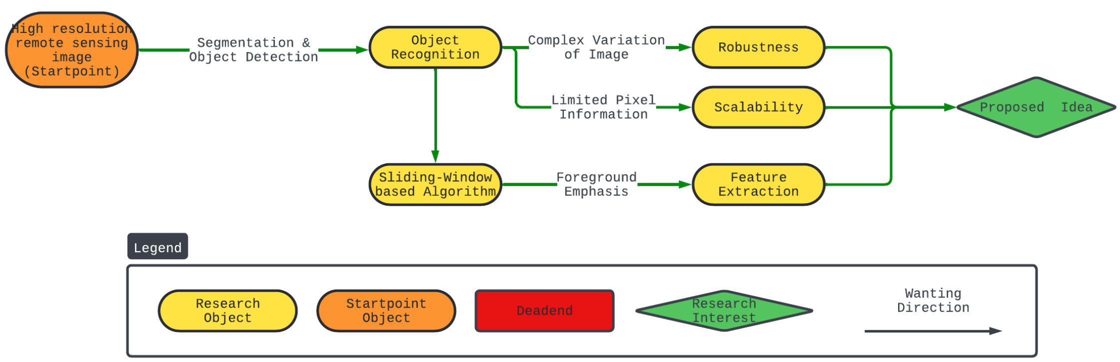

Figure 2: Wanting Structure for Scott et al. (2015)

In the following analysis, due to the space limit, we will no longer provide detailed reviews of the content of the papers. Instead, we will present flowcharts and analyze them based on the nodes and edges. There are two additional papers published by researcher G as first author within the first three-year window. The structure of wanting displayed in Figure 2 is quite streamlined, as it is a short conference paper focusing on explaining engineering details without introducing much-related research (Scott et al., 2015). It is another paper centered on the processing of large-scale high-resolution remote-sensing images. However, unlike the previous paper, it does not focus on building a computational framework but instead addresses a specific object recognition problem.

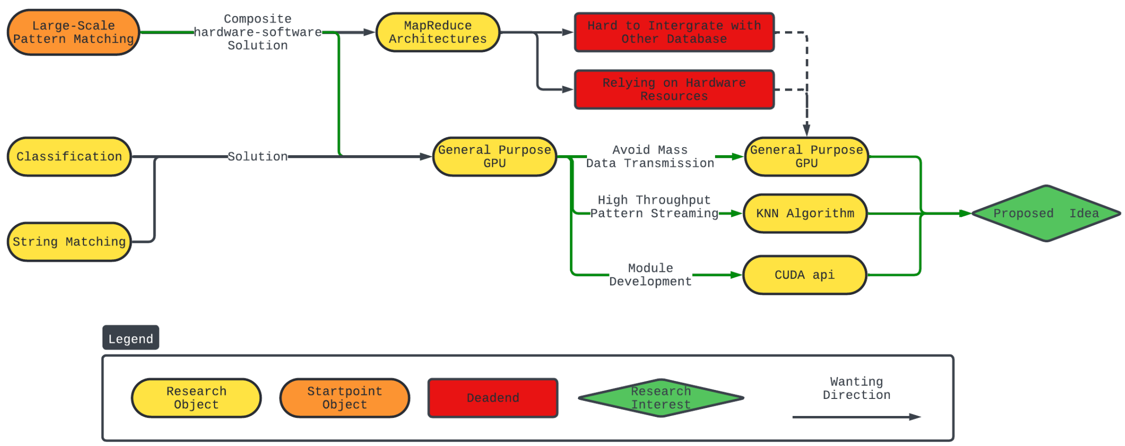

Figure 3: Wanting Structure for Scott, England, et al. (2014)

The third paper represented by Figure 3 is not directly related to high-resolution remote sensing images but returns to the theme of constructing high-performance computing frameworks using GpGPU(Scott, England, et al., 2014). We can also observe comparisons with other solutions for similar problems, demonstrating a mode of borrowing intuition from other contexts to adapt solutions.

During the first three-year window, researcher G mainly focused on the processing of high-resolution remote sensing images, the construction of computing framework under high-throughput conditions, and the application of GpGPU and related architectures. His structure of wanting reveals common characteristics of computer scientists, such as emphasizing differentiation from similar results and being adept at transferring solutions from similar tasks, which is the product of his intuition. He also shows some personal agency, focusing more on constructing end-to-end, high-performance computing frameworks rather than optimizing specific modules or algorithms.

Through these three representative papers, we can also observe how the researcher's intuition and agency are expressed within the object and wanting connections. The researcher's agency is particularly evident in the starting point of the chain of objects. Typically, researchers choose starting points where they have extensive engineering experience and are highly familiar with a set of objects. They understand the surrounding context of these objects and know what current research in this area entails and demands. More importantly, the chosen starting point acts as a signifier of their epistemic interest, indicating and justifying the aspects they are committed to pursuing. The starting point reflects a researcher's agency, as seen in G's commitment to an end-to-end high-performance framework, which helps explain his enthusiasm for deploying various models within such frameworks.

In contrast, intuition often manifests through the wanting connections, specifically through analogies, adaptations, and critiques of curated connections found in past literature. This process lends significance and credibility to the projection of their experiments.

Based on this understanding, we can infer that while this author's research objects evolved over the three years, there was no significant adjustment in their epistemic faculties. This consistency is evident as the starting points of his research align closely with those in his previous papers (e.g., large-scale frameworks and remote satellite image processing). Moreover, the changes observed in his conceptual diagrams are primarily replacements of nodes, without altering the core wanting connections, which remain focused on scalability and cost reduction. Although the nodes responding to the wantings changed, the content of the wantings themselves remained relatively consistent. This indicates that during this period, researcher G's understanding of the current needs within the field and the ways these needs could potentially be addressed remained relatively stable. In other words, his intuition was relatively fixed. In summary, by observing the relatively consistent starting points and wanting connections, we can infer that although the researcher shifted his research interests and objects during this three-year window, an analysis of his project content reveals that his epistemic faculties did not undergo significant change. His intuition and agency remained focused within a relatively stable domain and targeted specific objects. Therefore, we classify this type of interest shift as a local transition.

3.3 Next Three-year Window and Nonlocal Transition

In the three papers published during the following three-year window, we can clearly see that researcher G began to focus on using DCNN to replace the previous GpGPU- and SQL-based methods to address the problem of large-scale remote sensing image processing. When we delve into the specific objectual wanting structure of these three papers, we can observe the non-local transition process and the role collaborators played in it.

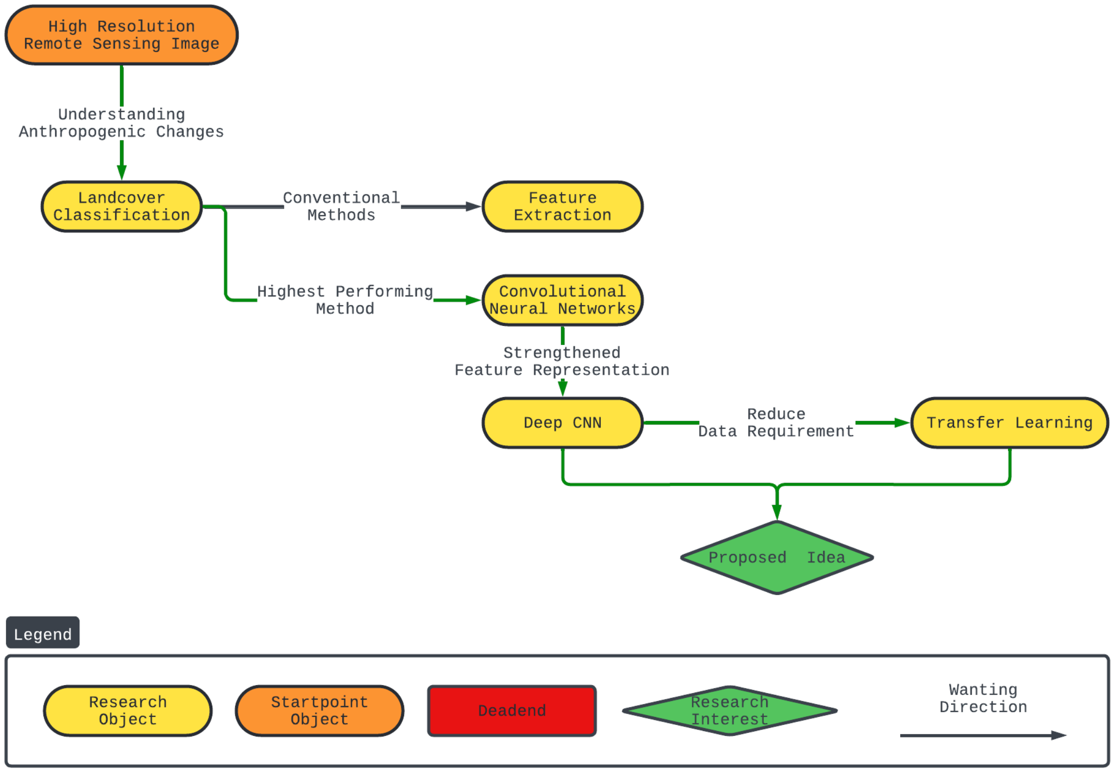

Figure 4: Wanting Structure for Scott, England, et al. (2017)

Starting with the first paper as represented by Figure 4, which has a relatively streamlined objectual wanting structure, researcher G merely outlined the direct path leading to the core interest. In this paper (Scott, England, et al., 2017), G replaced the previous GpGPU and traditional algorithm (FE/KNN) approach with DCNN to solve both the image processing and computational efficiency challenges. However, unlike medical imaging, remote sensing imagery suffers from a significant lack of labeled data, so G used transfer learning to fulfill this newly emerged wanting. Although this paper explores new objects such as DCNN and transfer learning, these objects belong to very similar community categories as the previously used GPU, HPC, and related methods. Therefore, compared to G's work in the previous three-year window, this project largely repeated his past use of agency and intuition, demonstrating a local transition in research interest.

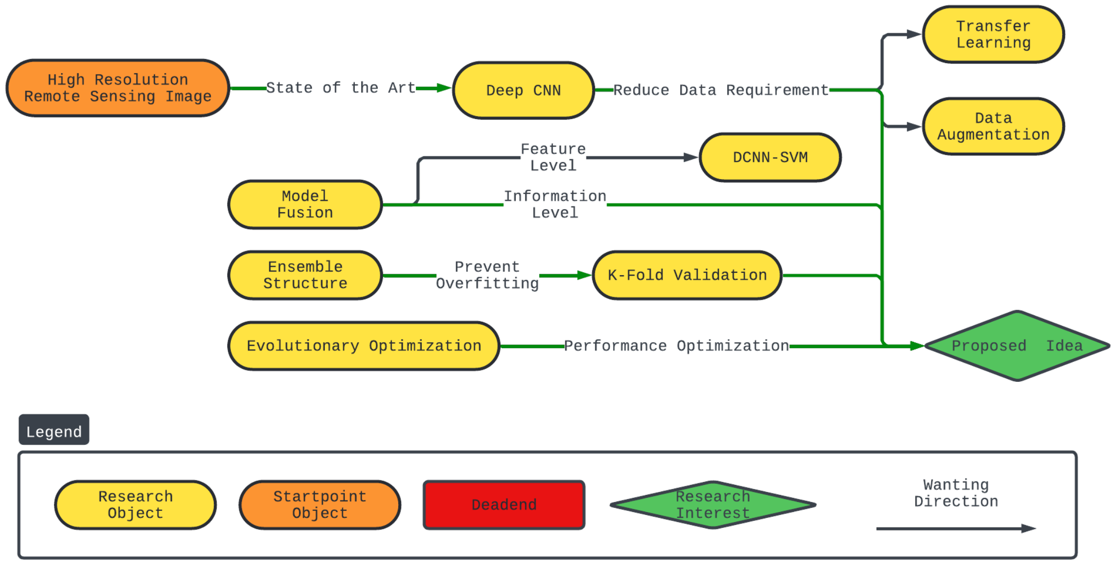

Figure 5: Wanting Structure for Scott, Marcum, et al. (2017)

This situation changes significantly in G's second paper during the second three-year window (Scott, Marcum, et al., 2017). As displayed by Figure 5, G continues to use DCNN to build the paper's interest, but the application of DCNN becomes much more complex. Given the lack of data in the field of remote sensing imagery, G first reviews two methods to mitigate this issue with DCNN (including the transfer learning approach he used previously) and then proposes a new approach. He borrows the concept of model fusion, where predictions from multiple models are combined and results from multiple models are integrated. Additionally, G applies evolutionary optimization to optimize the fusion model. To address potential overfitting due to data scarcity in model fusion, G incorporates k-fold cross-validation, borrowed from ensemble structures with similar architectures, to enhance data efficiency.

These new objects—model fusion, k-fold cross-validation, and evolutionary algorithms—all have significantly different domain affiliations compared with the original objects, making them difficult to identify from the literature previously familiar to researcher G, unlike DCNN. If we examine how these objects were introduced, two noteworthy phenomena emerge. First, in this case, new objects like DCNN are not only responders to existing objectual wantings but also generators of new objectual wantings. Many newly introduced objects aim to address wantings created by DCNN. These wantings did not exist in the previous objectual wanting structure. Second, researchers in this structure have completely different starting points for their chains. In contrast, researchers who focus only on local transitions exhibit clear differences in these aspects. Their new objects typically appear as satisfiers of pre-existing wantings rather than as creators of new wantings. Moreover, their chains' starting points tend to be old and fixed.

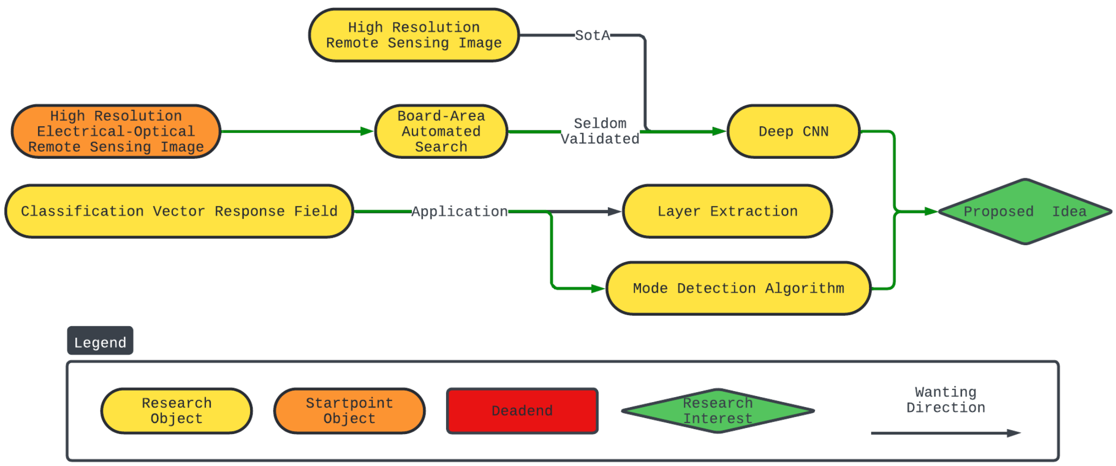

Figure 6: Wanting Structure for Scott et al. (2018)

From Figure 6,we can see that the third paper is also a highly streamlined conference paper (Scott et al., 2018). The Classification Vector Response Field (CVRF) is a byproduct of deep classification networks, and like the Mode Detection algorithm, it is an object with a domain affiliation that differs significantly from G's prior work. G's structure of wanting in this paper continues to exhibit the two core features mentioned earlier. First, G addresses the wanting associated with CVRF, specifically the challenge of effectively utilizing CVRF. Additionally, CVRF marks the starting point of a chain originating from a significantly different source.

In these three years of research, it is evident that as G's research objects and interests shifted, there was also a change in how he developed his research interests. His epistemic faculties evolved accordingly. First, his interest in constructing end-to-end high-performance frameworks diminished, as he noted in his papers, "Deep neural networks are the optimal solution for large-scale high-resolution image processing.(Scott, Marcum, et al., 2017)" Consequently, he focused more on the challenges associated with deploying and training DCNN networks, particularly the issue of insufficient training data[4]. He remained committed to high-performance, large-scale processing of remote sensing images, but here, DCNN not only acted as the solution but also generated new challenges. He anchored his agency in

[4]For potential confusion, in remote sensing image processing, while there is an abundance of remote sensing images for analysis and recognition, reliable labeled data is scarce

the new wanting unfolded by these objects (the lack of training data). Second, the curated wanting connections borrowed from existing literature have also changed. For example, in Scott, Marcum, et al. (2017), he mentions the ability of ensemble structures to address overfitting and the iterative capabilities of genetic optimization strategies. And in Scott et al. (2018), he leveraged the potential of the CVRF byproduct. These examples illustrate that the source of his intuition has significantly shifted. The emergence of many new wanting connections indicates that he not only observed and understood a variety of new ideas but also quickly translated them into engineering validations. He has markedly developed intuition related to new objects, which, in turn, formed the foundation for new research interests. In his research over these three years, he not only shifted his research interests but also transformed the epistemic faculties that generate these interests. We refer to this type of interest transition, which encompasses both intuition and agency, as a non-local transition.

In summary, we propose that the transformation of research interests does not necessarily entail a change in epistemic faculties, which differentiates non-local transitions from local transitions. These distinctions manifest in two notable characteristics on the conceptual diagrams we developed:

The first characteristic, where new objects both respond to existing wantings and generate new ones, illustrates how a researcher's intuition evolves. As researchers encounter new objects that challenge their prior knowledge or methods, their intuition is reshaped, and they can generate new research questions from them. This dynamic allows them to anticipate new challenges and opportunities that arise from the interaction of new objects, refining their ability to engage with unfamiliar concepts and make informed decisions.

The second characteristic, the introduction of new starting points for the chain, is closely related to the researcher's agency. By incorporating objects from different community affiliations, researchers demonstrate their capacity to expand their influence upon the core-set surrounding the new objects. This shift in agency reflects the researcher's willingness to adapt their role, stand for new approach, and explore new avenues, all while maintaining a coherent direction for their research.

These changes in intuition and agency enable the researcher to navigate non-local transitions more effectively. If we look at researcher G's case, we can identify three names that appear repeatedly in his projects starting from the second three-year window, indicating stable and intense collaborative relationships that provided a solid foundation during his exploration. Although objects like DCNN did not appear in the past work of these recurrent collaborators, we can see these objects—'model fusion, evolutionary algorithms, ensemble learning, and mode detection algorithm'—in the projects they each led during the three-year window. These are also key objects that G engaged with during his exploration. This suggests that these collaborative relationships fit the ‘advancing together’ type of collaboration mentioned in the interview analysis. Such relationships are crucial for helping researchers adapt and grow in new epistemic domains.

In this case study, we analyzed the research trajectory of researcher G by examining the structure of objectual wanting in his publications. Specifically, we tracked how multiple chains of wanting converged into a core research interest in a single paper and how his research objects and methodologies evolved over sequence of papers. We observed that during the first three-year window, G focused primarily on remote sensing image processing, high-performance computing, and GpGPU applications, while in the second three-year window, his focus shifted towards using DCNN to address challenges in large-scale remote sensing image processing. This transition marked a significant non-local shift, especially in the second and third papers, where G integrated new methods such as model fusion, evolutionary algorithms, and cross-validation—objects with domain affiliations distinct from his prior work.

This section’s analysis examined the process of research interest transition from the perspective of research objects. We introduced the concept of non-local transitions marked by shifts in object-level epistemic faculties. Additionally, we suggested the significant role that key collaborative relationships play in aiding researchers to adjust their epistemic faculties. In the next chapter, we will shift our focus to the local and non-local transitions of research interests at a macro level, using quantitative research to explore the role of collaborative relationships in these processes.

4 Recurrent Collaboration and Object Transition

In the previous section, we identified two types of interest transitions, distinguishing between local and non-local transitions based on whether researchers reformed their epistemic faculties. Additionally, we observed similar interest transitions among important collaborators of the researchers, suggesting the role of collaborators in supporting researchers’ transition of interests. In this section, through a macro-level analysis, we aim to further investigate the impact of the quantity and quality of collaborative relationships on researchers’ interest transitions. We aim to deepen our understanding of the knowledge production process, particularly in examining how scholars overcome epistemic challenges in a field characterized by highly active and dynamic research activity alongside frequent knowledge updates.

4.1 Collaboration and Object Engagement

4.1.1 Trace Researcher's Publication Sequence

Our quantitative analysis is based on bibliographic data from the DBLP-D3 (the dblp team, 2022; Wahle et al., 2022) dataset, which suits well for mass study in the field of Computer Science[5]

From DBLP-D3 databset, each scientist's research trajectory could be represented by a sequential publication record, accompanied with their demographic information like title, abstract, publication date, authors, number of citation, etc. Hence, each researcher's engagement with research objects and collaborative relationships can be identified and quantified from this publication sequence.

4.1.2 Detect Object Engagement

For the identification of research object engaged, we do not adopt common classification schemes like Field of Study (FoS) from Microsoft Academic Graph (Färber, 2019) or Semantic Scholar (Ammar et al., 2018; Lo et al., 2020), but instead use Computer Science Ontology (CSO) classifier (Salatino et al., 2020)[6].

With the help of the CSO identifier, we input the content of a paper and obtain the CSOs mentioned in it. This study did not perform this process manually but instead matched the D3 dataset with existing identification results. By doing so, we were able to determine the research objects authors engaged with in projects.

4.1.3 Relate Collaborative Relationship with Object Engagement

We select scientists with at least three years of first-author publication history as our research subjects. Similar to our previous analysis of researcher G, we primarily focus on examining the published works of researchers within two consecutive three-year windows. Similarly, as in the previous section, our subsequent approach will first focus on whether there has been a change in the researchers' research objects and then delve deeper into understanding the types of those changes. When examining their object engagement and collaborative relationships, we only considered publications where they were listed as the first author. For these researchers' trajectories, we compare the differences between their object engagement in the next three years and their engagement in the previous three years to quantitatively assess the extend to which they transition their interest on research ob-

[5] For detailed information about the DBLP-D3 dataset and the reasons for selecting it, please refer to the I section in the appendix

[6] For detailed information about the CSO identifier and the reasons for selecting it, please refer to the II section in the appendix

jects. Additionally, we calculated which new collaborators participated in the projects they first-authored during the next three years, as well as the number of times each collaborator contributed to these projects. In the following parts, the ”previous three years” will be called ”observation window”, and the ”next three years” as ”interaction window”.

Finally, we use DOE (Distance of Object Engagement) to measure the extent of a researcher’s transition in research objects across time windows. The DOE value reflects the change in the number of papers related to each research object (CSO) across different time windows. For each CSO, if the number of publications increases in the interaction window compared to the observation window, the absolute difference is added to the DOE. Similarly, if the number of publications decreases, the absolute difference is also added. Therefore, any change in the number of publications for a specific research object, whether an increase or decrease, will result in an increase in the DOE value. A higher DOE value indicates a more significant shift in research interest, while a lower value suggests that the research objects remained relatively consistent from the observation window to interaction window[7].

In addition, we will examine the new collaborators these authors had in their first-authored projects during the interaction window. We will count the number of new collaborators and the number of times each collaborator contributed to these projects for further analysis.

A total of 35,372 researchers meet our selection criteria out of 516,897 authors that have published during the interaction window. Figure 7 preliminarily reflects the researchers’ active publications, collaboration change, and interest-switch frequency in the field of computer science, which aligns with the findings of previous studies.

Variables	Coefficients	Standard Errors	t-values	p-values
Intercept	-1438.10	51.47	-27.94	0.00
New Collaborators	2.26	0.03	84.02	0.00
Productivity	6.32	0.05	119.87	0.00
Impact	-0.00	0.00	-1.12	0.26
Hindex	0.28	0.04	7.80	0.00
Age	0.14	0.05	2.74	0.01
Career Stage	0.58	0.06	10.13	0.00
Team Size	-2.39	0.18	-13.36	0.00
R Squared	0.60			

Table 1: OLS Regression Results of DOE

[7] Please refer to III section in the appendix for detailed description and justification on the computational scheme of Distance of Object Engagement.

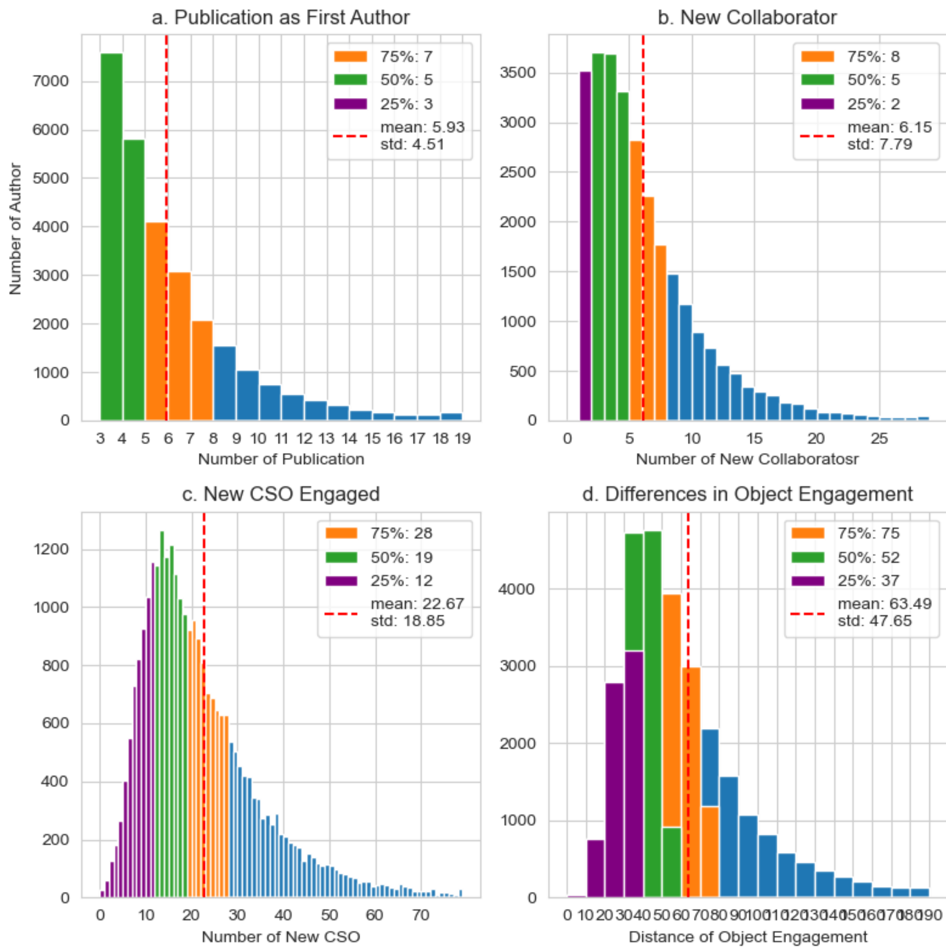

Figure 7: The figure illustrates that research activities in the field of computer science—such as first-author publications, initiating new collaborations, and shifting research objects—are widely active across most disciplines (Piro et al., 2013; Zeng et al., 2018).**a** shows that as the number of publications increases, the number of researchers decreases, following an approximate power-law distribution (Bornmann, 2024); around 50% of researchers published approximately five papers during the three-year observation window.**b** demonstrates that researchers tend to establish relationships with around five new collaborators in their first-author projects.**c** reveals that exploring new research objects is a common and intensive practice, with most researchers engaging with approximately 20 new objects. The shift in their research focus is measured in**d**, indicating that most researchers undergo considerable changes in research objects, with an average DOE (Distance of Object Engagement) value around 52. These data align with findings from previous research and provide a fundamental depiction of research activities in the field of computer science.

Our findings (as shown by Figure 4.1.3) align with those from previous studies and our interview that, changes on research interest is often accompanied with new collaborative relationships (van der Wouden & Youn, 2023; Venturini et al., 2023; Zeng et al., 2022). We controlled factors identified in previous research that may affect a researcher's exploration of new objects[8]. The model has an R-squared value of 0.60, suggesting that the model explains 60% of the variance in DOE, indicating a good fit. New collaborative relationships has a positive coefficient (2.26), indicating that an increase in new collaborators leads to a significant rise in DOE. It is highly significant with a t-value of 84.02 and a p-value of 0.00.

To further explore the impact of new collaborative relationships on object transition, we used a GBDT (Gradient Boosted Decision Tree) model to fit the DOE. GBDT is particularly effective at capturing nonlinear interactions between variables and provide reliable simulation for social science studies[9]. By studying the trend of DOE as the number of new collaborations changes, based on randomly sampled data sets (each time selecting 10% from the total sample), we obtained robust predictive results (as shown in Figure 8).

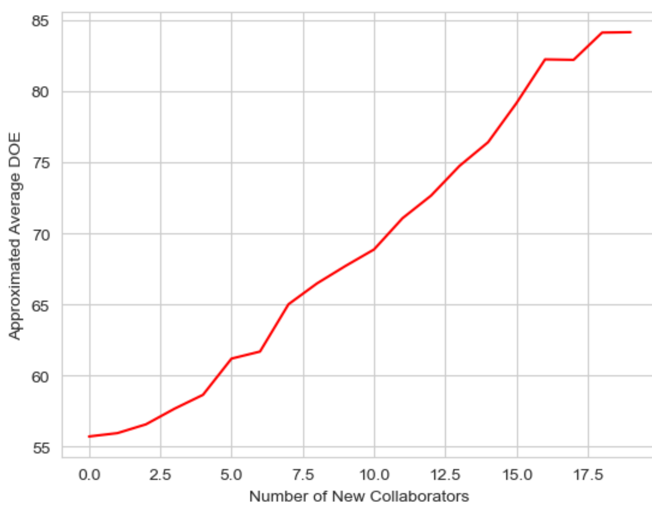

Figure 8: GBDT simulation results shows that, as the number of new collaborators increases from 0 to 20, the DOE also rises significantly from 56 to 84.

Figure 8 displays a significant and substantial positive correlation between the number of new collaborators and the extent to which they change their research interests. The result of

[8]Based on previous research, we have controlled as many important variables as possible that could influence topic switch and interest transition. Referring primarily to the papers(van der Wouden & Youn, 2023; Venturini et al., 2023; Yin, 2024), we have taken steps to control for conditions and confounding factors (productivity, scholarly impact, hindex, age, career stage, team size).

[9]GBDT is well-suited for this kind of analysis because it effectively captures complex, nonlinear relationships between variables. Its robustness in handling diverse data patterns makes it widely use in multiple areas of studies (Han et al., 2023; Neelakandan & Paulraj, 2020; X. Zhang et al., 2022).

the simulation indicates that, with other conditions remaining constant, new collaborative relationship is a crucial factor in researchers transition to new research objects.

4.1.4 Recurrent Collaboration and One-time Collaboration

To further explore the impact of different types of collaboration relationships on object transitions, we selected two distinct types of new collaborative relationships: recurrent collaboration and one-time collaboration. We define recurrent collaboration as collaboration that occurs four or more times[10], while one-time collaboration refers to collaborations that happen only once.

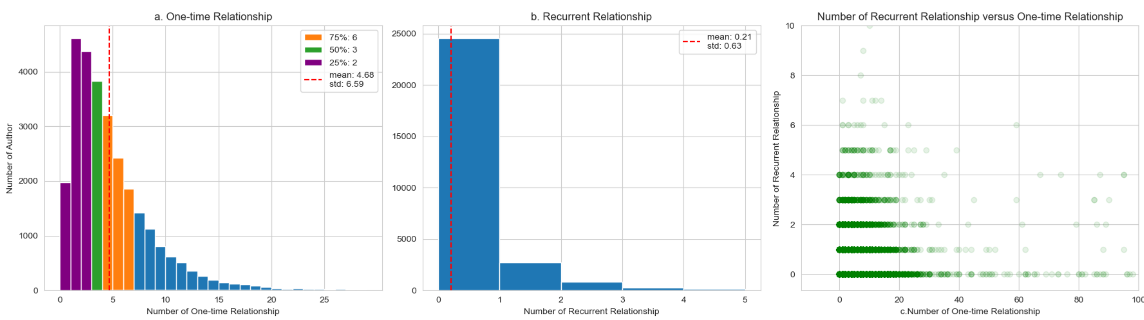

Figure 9: This figure shows the distribution of one-time and recurrent collaborations among researchers. **a** reveals that, on average, researchers establish one-time collaborations with 4 to 5 collaborators. This is close to the total number of new collaborators, indicating that most collaborative relationships are one-time engagements. In contrast, the number of recurrent collaborations is significantly smaller. **b** indicates that approximately 86% of researchers has no recurrent relationships, and only 5% of collaborators experiences more than one recurrent collaboration. In **c**, when the number of one type of relationship reaches a high enough level, it can crowd out space for the other type.

Figure 9 indicates that researchers tend to form significantly more one-time relationships than recurrent ones. Previous literature has reached a consensus that new collaborative relationships often accompany switched research topics. However, there is still debate regarding the influence of different types of collaborative relationships on topic switching. Some argue that repeated collaborations may hinder researchers from exploring new directions and lead to negative topic switch(Dahlander & McFarland, 2013; M. Liu et al., 2022). While others hold the opposite view, claiming that recurrent collaboration provides sites for knowledge spillover (van der Wouden & Youn, 2023; Venturini et al., 2023). In this study, I explore how one-time and recurrent collaborations affect a scientist's transition to new research objects.

[10] According to previous research, collaborations in the field of computer science that occur four or more times are associated with significantly stronger effects like knowledge spillover, topical contagion, etc(van der Wouden & Youn, 2023; Venturini et al., 2023). Thus it is a reasonable choice for a threshold.

Similarly, I conducted a regression analysis on the influence of the number of one-time and recurrent relationships on scientists' DOE.

Variables	Coefficients	Standard Errors	t-values	p-values
Intercept	-1238.05	50.73	-24.41	0.00
Recurrent Collaborators	16.21	0.29	56.24	0.00
One-time Collaborators	2.07	0.03	68.05	0.00
Productivity	6.43	0.05	124.67	0.00
Impact	-0.00	0.00	-0.34	0.73
Hindex	0.16	0.04	4.42	0.00
Age	0.11	0.05	2.21	0.03
Career Stage	0.51	0.06	9.08	0.00
Team Size	-1.91	0.17	-11.05	0.00
R Squared	0.62			

Table 2: OLS Regression Results of DOE

As shown by Figure 4.1.4, the linear regression model has an R-squared value of 0.62, suggesting that the model explains 60.2% of the variation in DOE, indicating a good fit. The results show that both one-time relationships (coef = 2.07, p ¡ 0.001) and recurrent relationships (coef = 16.21, p ¡ 0.001) have a significant positive impact on DOE. Recurrent relationships have a much larger coefficient, indicating that repeated collaborations contribute more significantly to object engagement. Other control variables, such as prior collaborations and team size, also showed significant effects.

Similarly, a GBDT simulation is conducted, and the results of the GBDT model brought different insights. Figure 10 shows that, with other conditions controlled, the number of recurrent relationships has a much larger impact on object transitions than one-time relationships. Additionally, the effect is most pronounced when recurrent relationships emerge (from 0 to 1 or 2), while further increases in the number of recurrent relationships show diminishing returns. This suggests that the mere presence of recurrent collaborations is crucial for fostering object transitions, and additional increases in the number of such collaborations have a less significant impact. There is a diminishing marginal effect here.

4.2 Localization of Research Objects

Merely knowing that recurrent collaborative relationship is an important factor in scientists' transitions to new research objects is not enough. What we are interested in here is how these recurrent relationships facilitate object transitions, and what happens during the progress. This requires linking back to the previously discussed notion of reconstruction of epistemic faculties. Recurrent collaborations provides preferable conditions for researchers

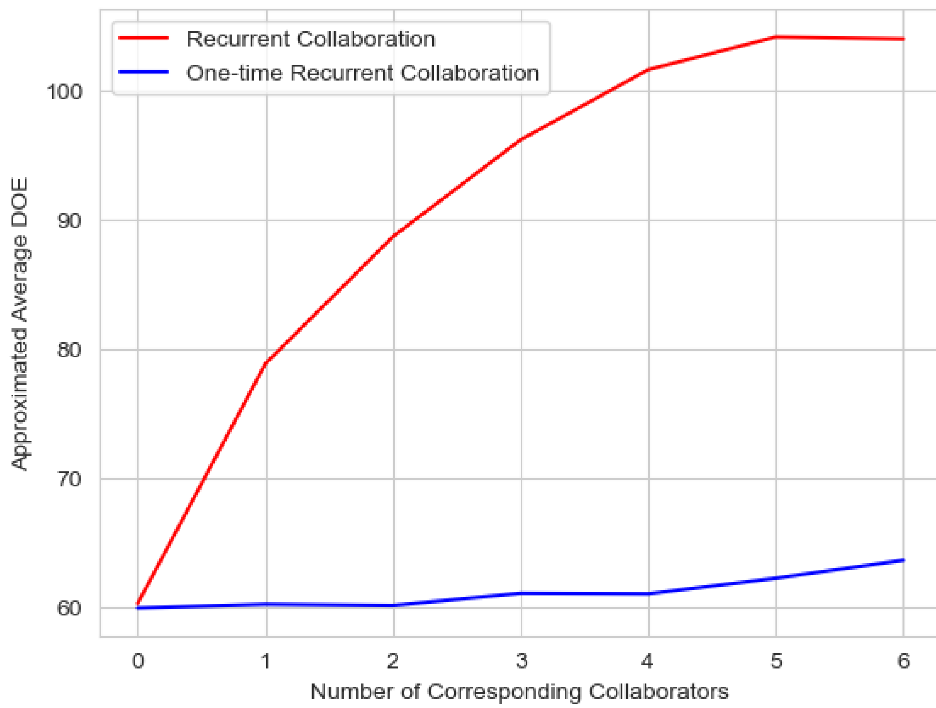

Figure 10: GBDT simulation results shows that, as the number of recurrent collaborators increases from 0 to 6, the average DOE rises from 60 to more than 100. As the number of one-time collaborators rises, the average DOE rises from 60 to 64.

to develop intuition and agency upon objects they are not familiar with.

We cannot overlook the cognitive and practical challenges scientists face when undertaking projects that involve transitioning to a new research areas and publishing their results. As one interviewee mentioned above, she needed her collaborators to spend hours and hours explaining in detail what the problems in the medical field actually were and what these issues truly meant within the context of the medical domain. On contrast, computational medical research today is vastly different from what it was a decade ago. First, it has evolved into a mature and complex discipline, where knowledge and technology from various fields have deeply intersected. Second, for researchers with different backgrounds, a lot of alignment work and boundary objects have facilitated relatively quick establishment of intuition and agency. In the previous section's analysis, the local transition that researcher G experienced during the observation window and the nonlocal transition between the two windows presented distinct epistemic, informational, and engineering challenges. These transitions also had markedly different impacts on both the individual researcher and the research community.

Reflecting on the case study of researcher G, there is a noticable difference between local and nonlocal transitions: the objects involved in local transitions are often found within similar bodies of literature, which is not the case in non-local transition. Here, the question would be: how we could quantitatively identify and measure the locality here? How can we distinguish between relatively easy (local) transitions of interest and the hard (non-local) transitions that require significant adjustment of epistemic faculties to achieve?

4.2.1 Engineering Sites and Communities of Research Objects

The affiliation of research objects to specific fields or communities has long been an important topic in the social study of science, and so does its measurement and quantification. In previous studies, some approaches have directly used the co-occurrence of objects in papers to determine the relationships between them (Foster et al., 2013), while others have employed parameterized models or vector-embedding methods to assess whether objects belong to the same field or whether their combination is considered 'common' (F. Liu et al., 2023; Shi & Evans, 2019; S. Zhang et al., 2023). Here in our work, we constructed a co-occurence network and derived a measurement to quantify the epistemic boundary between research objects.

Following previous studies using the CSO, we construct a network of relationships between research objects based on the frequency with which CSOs co-appear in papers. In this network, each node represents a CSO, which has been stabilized over time through long-term research(Knorr-Cetina, 2000). The edge weights between nodes represent the frequency with which they co-appear in papers. The more frequently two CSOs appear together in the same project, the stronger their knowledge accumulation and practical association, shaping relatively tight knowledge communities within the CSO network. Then, we used community partition algorithm to divide CSOs into communities where weights of edges within communities is maximized and edges across communities are minimized.

As a result, we constructed a CSO network based on the co-occurrence of CSOs during the observation and interaction windows. This network consists of 10,786 nodes and 5,841,680 edges. The network is divided into 65 communities of various sizes, with a modularity value of 0.42, indicating a moderately strong community structure. Figure 11 illustrates the affiliations and the strength of connections among the 65 communities.[11].

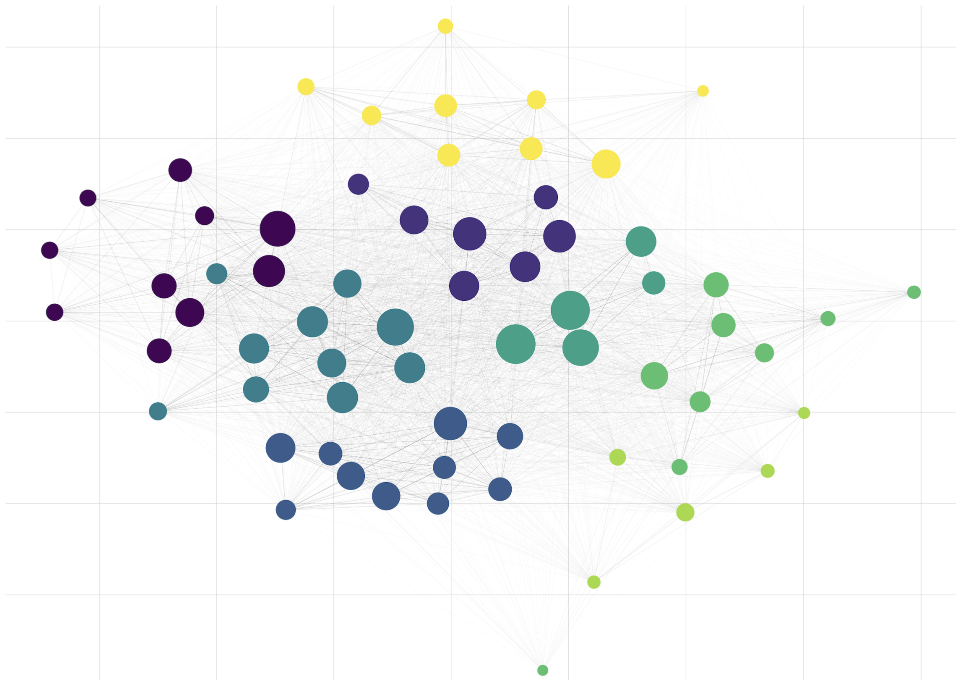

Figure 11: All 10,786 CSOs underwent two rounds of Louvain community division, achieving optimal classification results. This process produced 8 primary communities and their 65 subordinate secondary communities. The figure presents a visualization of the classification outcome. Nodes with the same color indicate their belonging to the same primary community. The presence and thickness of edges between community nodes represent the frequency of co-occurrence between the corresponding CSOs.

Based on these communities, we can determine the extent to which objects are epistemically or practically connected. We do not measure this connection by simply determining whether objects belong to the same community; rather, we infer their connection through

[11]For detailed description of network construction and community partition, please refer to IV section in the appendix

whether they share similar community affiliations. This is because many objects that are frequently juxtaposed in epistemic or practical contexts don't often appear in the same paper simultaneously, as they may not constitute a research interest. Such "silent" objectual connections cannot be directly identified through co-occurrence or shared community membership but can be inferred through their similar community affiliations. I will illustrate this point with an example as follows:

I will first introduce two large CSO communities: communities No.10 and No.12. Community No.10 centers around wireless communication techniques. It consists of 735 CSOs, covering the theoretical underpinnings (such as Gaussian channels, channel state information, and outage probability) and practical aspects (e.g., antenna systems, beamforming, and error correction techniques) of modern communication systems. Community No. 12 focuses on network construction and optimization. It encompasses a wide range of concepts related to internet protocols, peer-to-peer (P2P) networking, sensor networks, and vehicular networks. It consists of 778 CSOs highlighting the optimization of communication networks, especially in dynamic and distributed environments like vehicular networks, wireless sensor networks, and the Internet of Things.

From community No.12 introduced above, wireless sensor networks and energy-aware routing are two strongly connected CSOs. Wireless Sensor Networks (WSNs) are made up of small sensor nodes that communicate wirelessly to collect data from their surroundings, like temperature or humidity. These sensors often run on batteries, so it's important to use their energy wisely. Energy-aware routing is a method used to choose the best paths for sending data between sensors. It looks at how much battery power each sensor has left and picks routes that save energy. This helps make sure the sensors can keep working for as long as possible without running out of power too quickly. So, energy-aware routing helps WSNs last longer and work more efficiently. CSOs that appear in the same community or have a high co-occurrence frequency often share a strong epistemic connection. Scientists naturally recognize their relatedness in terms of knowledge structure, as well as the contexts or problems in which they commonly occur. These connections correspond to "local" connections in knowledge production.

However, another type of local connection that is usually overlooked, as I mentioned earlier, involves CSOs that, while not belonging to the same community, share similar community affiliations. For example, "optical wireless system (OWS)" is a CSO from community No.10, while network coding forms a crucial component of projects on Network Coding, which is from community No.12. Optical Wireless Systems (OWS) use light (like infrared or visible light) to transmit data wirelessly, offering high-speed communication over short distances. However, these systems can be affected by interference, obstacles, or signal loss. Network coding is a technique that improves data transmission efficiency by allowing the mixing of data packets during transmission, helping to recover lost data more effectively. These two CSOs often come together in environments with high data traffic, such as indoor communications, data centers, or free-space optical systems. Network coding techniques helps Optical Wireless Systems deal with challenges like signal interference or blockages by improving data reliability and efficiency, ensuring smoother communication even when parts of the signal are lost or disrupted.

A similar community affiliation vector often indicates that the contexts in which these CSOs combine are dispersed across different fields or interdisciplinary domains. Although they belong to different communities and appear together less frequently in the same papers, they jointly contribute to the configuration of important contexts and problems (such as indoor communication, hybrid-RF systems, etc.). This can be reflected in related papers, books, and researchers' portfolios. Experienced researchers in the OWS field can easily gather information about network coding from nearby literature and colleagues, and vice versa. While these CSOs may be challenging to combine productively in a single study, they are important epistemic components that contribute to the overall configuration of the context. Therefore, we classify similar community affiliations as a form of local connection. Similar affiliations represent similar application contexts. These actual engineering contexts involve a significant amount of alignment work and key boundary objects, which facilitate collaboration and problem-solving across different areas.

Figure 12 shows the relationship between co-occurrence frequency and community affiliation differences among CSO pairs. The figure clearly demonstrates that the similarity of community affiliation sets an upper bound for co-occurrence frequency: only CSOs with similar community affiliations can achieve high co-occurrence frequencies. Additionally, CSO pairs with high co-occurrence frequencies always exhibit similar community affiliations. This suggests that having a strong epistemic connection is a necessary but not sufficient condition for a high co-occurrence rate. Most objects that are closely related in knowledge or practice do not frequently appear together in the same paper. Only a few combinations become the focal points of research interest.

The reason we measure the community affiliation of objects is to better capture the reality of research practices. We aim to assess how much unfamiliarity a researcher encounters when transitioning to a new research object (such as machine learning and healthcare before computational healthcare became mature). This helps avoid misclassifying closely related objects (such as OWS and coding system) as part of a non-local transition when, in fact, they are strongly connected. Detailed conceptual diagrams are difficult to extract on a large scale from databases; therefore, we will primarily focus on whether objects explicitly or implicitly appear in similar situations and literature.

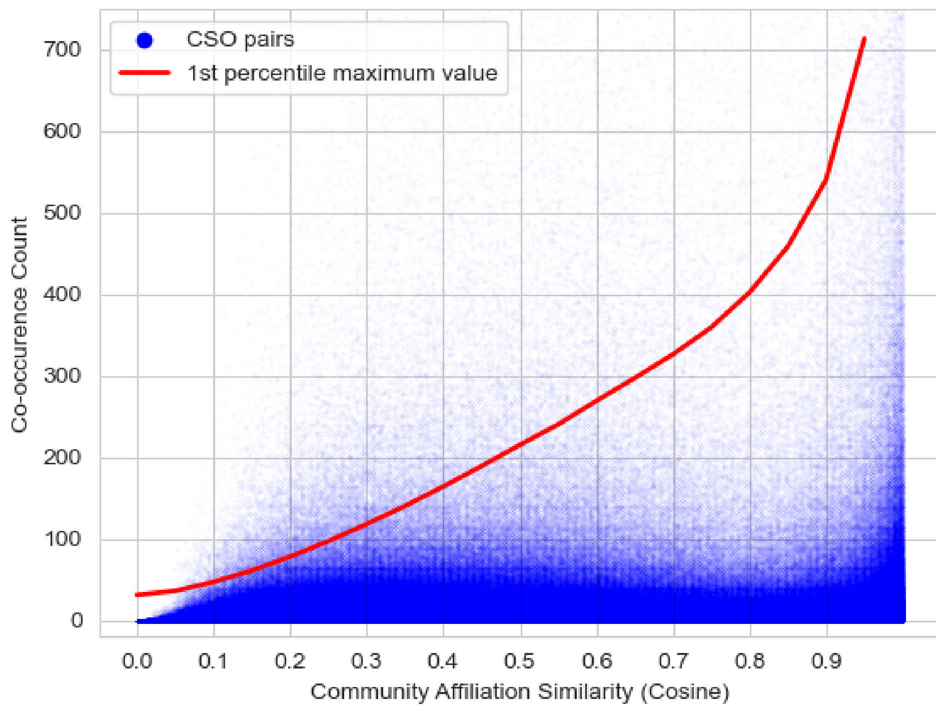

Figure 12: The relationship between the similarity of community affiliations among CSO pairs and their co-occurrence frequency. For each similarity value, the red line marks the 99th percentile of co-occurrence values.

4.2.2 Non-local Object Transition and Recurrent Collaboration

To identify scientists' non-local transitions, in addition to measuring DOE (Distance of Object Engagement), we will also measure their Distance of Community Affiliation (DCA). First, we measure each CSO's community affiliation by constructing a community affiliation vector, representing its co-occurrence frequencies with all 65 communities. This vector captures how strongly each CSO is associated with various communities. Researchers' Distance of Community Affiliation (DCA) is then calculated by comparing their community affiliation vectors during the observation window and the interaction window. The DCA is the sum of the absolute differences between these vectors, reflecting how much a researcher has shifted between different epistemic communities. A higher DCA value indicates a more significant shift in the researcher's focus on different community-affiliated objects, reflecting a more substantial epistemic transition. Conversely, a lower DCA implies more continuity and stability in the researcher's object engagements across time, even though they may have actually undergone significant objectual transitions. This is because transitions between objects within the same or similar community affiliations may not register as a high DCA. Thus, DCA specifically captures the degree of epistemic distance between the communities, rather than the magnitude of the objectual shift itself[12].

We can further argue that DCA measures the extent to which researchers need to reconstruct their epistemic faculties—intuition and agency—during object transitions. When there is no object transition, the change in their epistemic faculties is minimal. When they transition to familiar or adjacent objects (within a local range), some adjustment effort is required, but it is not substantial. However, when they transition to unfamiliar objects with scarce epistemic connections (in a non-local range), the challenges they need to overcome are much greater. Due to the various limitations scholars face, long-range transitions are often associated with greater innovation and unpredictability, as argued in past literature (Shi & Evans, 2019; Uzzi et al., 2013). However, it is important to note that they are not the same concept. Here, we are more focused on how many resources scientists can mobilize from knowledge content organization during object transitions and interest reformation, and further examine how collaborative relationships supplement scholars' agency when resources are scarce.

We used a linear regression model to examine how one-time and recurrent collaborations affect DCA, while controlling for baseline factors. The results in subsubsection 4.2.2 show that both one-time collaborations (coef = 0.521, p ¡ 0.001) and recurrent collaborations (coef = 9.354, p ¡ 0.001) have a significant positive impact on DCA, with recurrent collaborations having a much larger effect. This indicates that scientists who engage in recurrent

[12]Please refer to V section in the appendix for detailed description and formulas on the Distance of Community Affiliation.

Variables	Coefficients	Standard Errors	t-values	p-values
Intercept	-643.20	36.10	-17.82	0.00
Recurrent Collaborators	9.35	0.21	45.61	0.00
One-time Collaborators	0.52	0.02	24.09	0.00
Productivity	2.51	0.04	68.24	0.00
Impact	0.00	0.00	0.29	0.77
Hindex	0.22	0.03	8.75	0.00
Age	0.02	0.04	0.52	0.60
Career Stage	0.31	0.04	7.59	0.00
Team Size	-0.53	0.12	-4.28	0.00
R Squared	0.34			

Table 3: OLS Regression Results of DCA

collaborations tend to experience a greater shift in their research context (DCA), as compared to those involved in one-time collaborations. Other variables, such as productivity (coef = 2.505, p ¡ 0.001) and h-index (coef = 0.222, p ¡ 0.001), also positively influence DCA. Team size (coef = -0.527, p ¡ 0.001) shows a negative relationship, indicating that larger teams may inhibit significant transitions. Non-significant variables include impact and age. Overall, the model explains 33.5% of the variation in DCA, indicating a moderate fit.

Figure 13 show that the GBDT simulation results are largely consistent with the linear regression model. However, in this case, recurrent collaborations do not exhibit diminishing marginal returns on DCA. This suggests that each recurrent collaborator contributes similarly and significantly to the researcher's nonlocal transition, underscoring the sustained impact of recurrent collaborations on facilitating epistemic shifts across different research contexts. Each recurrent collaboration counts in this term.

To further investigate the relationship between collaboration and non-local transitions, particularly whether one-time and recurrent relationships lead to different types of object transitions, we controlled for the DOE variable and performed a regression analysis on DCA. This analysis will allow us to determine if recurrent collaborations are more likely to drive significant shifts in research contexts (non-local transitions) than one-time collaborations. Additionally, we may observe how different factors influence the depth of these transitions when DOE, which measures the shift in object engagement, is held constant. This can reveal whether recurrent collaborations and one-time collaborations lead to different types of object transitions, and how they impact researchers' preferences.

Figure 4.2.2 show that recurrent collaborations (coef = 1.123, p ¡ 0.001) have a positive impact on DCA, indicating that recurrent collaborations facilitate more non-local transi-

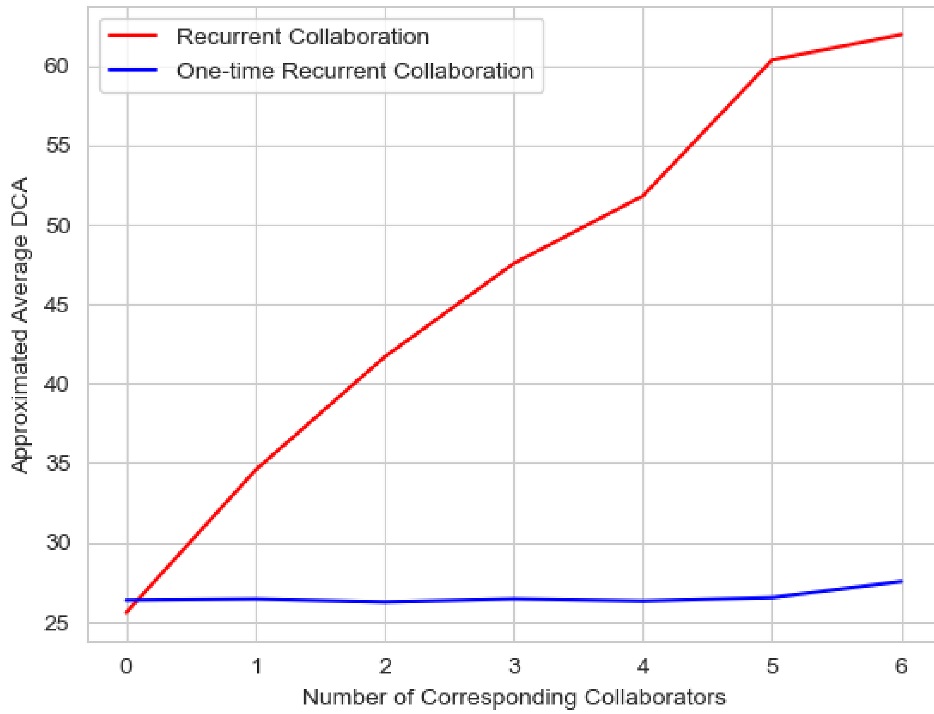

Figure 13: GBDT simulation results shows that, as the number of recurrent collaborators increases from 0 to 6, the average DOE rises from 25 to more than 60. As the number of one-time collaborators rises, the average DCA doesn't change much.

Variables	Coefficients	Standard Errors	t-values	p-values
Intercept	-14.63	25.56	-0.57	0.57
Recurrent Collaborators	1.13	0.15	7.43	0.00
One-time Collaborators	-0.53	0.02	-32.37	0.00
DOE	0.51	0.00	171.78	0.00
Productivity	-0.76	0.03	-23.74	0.00
Impact	0.00	0.00	0.76	0.45
Hindex	0.14	0.02	7.98	0.00
Age	-0.04	0.03	-1.51	0.13
Career Stage	0.04	0.03	1.58	0.11
Team Size	0.44	0.09	5.12	0.00
R Squared	0.34			

Table 4: OLS Regression Results of DCA with DOE Controlled

tions. In contrast, one-time collaborations (coef = -0.529, p ¡ 0.001) have a negative impact on DCA, suggesting that these relationships tend to be associated with less significant shifts in research context. Other factors, such as productivity (coef = -0.763, p ¡ 0.001) and team size (coef = 0.452, p ¡ 0.001), also exhibit significant and curious relationships with DCA when DOE is controlled. Overall, the model explains 67.4% of the variance in DCA, suggesting a strong fit. This regression result clearly indicates that scientists involved in recurrent relationships are more likely to make non-local transitions, while one-time relationships have the opposite effect. The GBDT simulation also supports this conclusion, as shown in Figure 14.

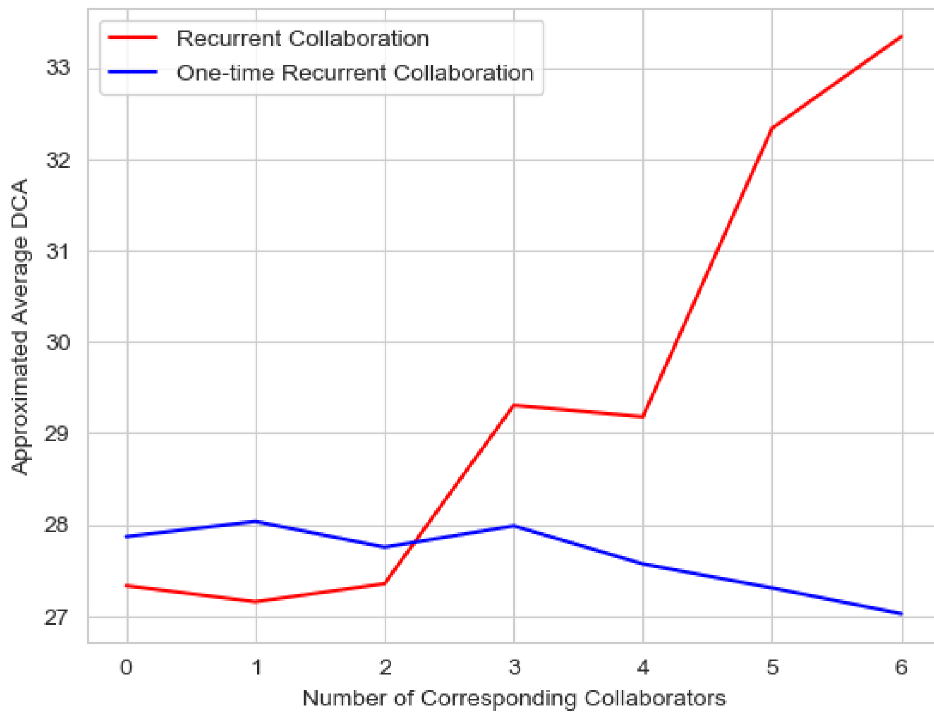

Figure 14: GBDT simulation results shows that, when DOE is controlled, as the number of recurrent collaborators increases from 0 to 6, the average DOE rises from 27 to 33. As the number of one-time collaborators rises, the average DCA decreased from 28 to 27.

4.3 Summary on the Object Transition Analysis

In this analysis, we investigated how different types of collaborations, specifically one-time and recurrent collaborations, influence researchers' transitions to new research objects. We measured researchers' object transitions using DOE (Distance of Object Engagement) to quantify changes in the number of publications related to various research objects across different time periods. We further introduced DCA (Distance of Community Affiliation) to capture how much a researcher shifted between different epistemic contexts. By using a combination of regression models and GBDT simulations, we analyzed the impact of new collaborations on DOE and DCA, with a particular focus on the effects of one-time versus recurrent collaborations.

Our results demonstrate that both one-time and recurrent collaborations significantly contribute to changes in a researcher's object engagement (DOE) and epistemic shifts (DCA), but recurrent collaborations have a much larger impact. The regression results show that recurrent collaborators promote non-local transitions, as indicated by a higher DCA, whereas one-time collaborators tend to contribute to more localized, less distant shifts. The analysis also revealed that recurrent collaborations provide consistent support for epistemic transitions without diminishing marginal returns, suggesting that each recurrent collaborator plays a crucial role in facilitating non-local transitions.

We extend the findings and hypotheses from our interview and case study analyses to a macro-level quantitative exploration, further examining the relationship between collaborative relationships and research interest transitions. Overall, this analysis underscores the significant role of recurrent collaborations in supporting researchers as they venture into new and unfamiliar research objects, indicating that such stable partnerships are essential for fostering profound epistemic shifts. In contrast, one-time collaborations often constrain researchers to more incremental changes, limiting the scope and depth of their transitions. These insights highlight the value of sustained, intensive collaborations in shaping researchers' exploration of new domains and facilitating their transitions to new fields.

Consistent with our earlier interview analyses, recurrent collaborations assist researchers in reconstructing their epistemic faculties—intuition and agency—during transitions to new research objects. This reconstruction is particularly vital when researchers encounter new fields where knowledge reserves are limited and boundary objects or alignment mechanisms are lacking. Through repeated and ongoing interactions, collaborators provide essential support, enabling researchers to cultivate their research interests in less familiar areas. Such stable partnerships lay a dependable groundwork that allows for smoother transitions and deeper engagement with novel research objects, thus enhancing the overall adaptability and growth of the research process.

5 Conclusion and Discussion

5.1 Conclusion

The study underscores the profound influence of collaborative relationships on researchers' transitions between research objects and the adjustments in their epistemic faculties—intuition and agency. From the interviews analyzed, it became evident that researchers rely on intuition, which helps them derive credible interpretation of ideas, and agency, marked by active commitment and project ownership, to navigate the uncertainties of their work. The interviews highlighted that collaboration serves as a critical channel through which researchers fine-tune these faculties. Collaborators can provide complementary intuition or enhance researchers' agency. The alignment of shared intuition and the reinforcement of agency fostered by collaborative relationships were shown to be particularly impactful during transitions to new research objects, facilitating smoother adaptations and greater innovation.

The case study of researcher G illustrated how these principles play out in actual projects. In the initial observation window, G's research projects were rooted in familiar engineering and computational contexts, with local transitions of research interest. These local transitions involved minimal change in his intuition and agency, as he consistently built on well-established objects within the same knowledge domain. However, in the subsequent interaction window, G's shift to deep learning and associated methods represented a non-local transition that required significant reformation of his epistemic faculties. The introduction of novel objects like DCNN and model fusion, which generated new challenges and opportunities, signified a reconfiguration of G's intuition and agency. This shift suggests how collaborative support played a pivotal role, as stable, repeated partnerships enabled G to navigate the challenges of adapting to unfamiliar research landscapes.

Quantitative analyses confirmed these qualitative findings, showing that recurrent collaborations had a stronger impact on researchers' transitions compared to one-time partnerships. Recurrent collaborations were particularly influential in facilitating non-local transitions, where the adjustment of epistemic faculties was necessary for success. The regression analysis and GBDT simulation demonstrated that scientists with stable, repeated collaborations were more likely to experience significant epistemic shifts and adapt effectively to new research contexts. These relationships provided the scaffolding needed for researchers to develop new intuition and agency, essential when moving into less familiar areas where alignment work and boundary objects were less readily available.

In contrast, one-time collaborations, while contributing to new insights and incremental advancements, often restricted researchers to more local transitions. These collaborations were less effective in promoting the epistemic reconstruction required for significant shifts. This finding aligns with interview insights that emphasized the value of "learning different minds" and "structuring" ideas during long-term collaborative efforts. Recurrent collaborations were found to provide a robust framework for such activities, enabling researchers to leverage diverse expertise while building stable epistemic foundations. This study highlights the importance of fostering long-term, stable collaborations to support researchers' development and capacity for innovative work across varied and challenging domains.

5.2 Discussion

While the current analysis provides valuable insights into how collaborative relationships influence researchers' transitions between research objects and the adjustments of their epistemic faculties, it is not without limitations. One major limitation lies in the reliance on bibliometric data and publication records, which can only approximate researchers' true interests and object engagement. Although the use of CSO classification and DOE/DCA metrics provides a structured approach to measuring object transitions, these measures do not fully capture the nuanced and subjective experiences of researchers' decision-making processes, particularly the affective and interactive aspects of intuition and agency. Furthermore, while we attempted to bridge qualitative insights from interviews and case studies with quantitative data, the alignment between these two approaches remains complex and may not fully encompass all factors influencing research transitions, such as institutional pressures, funding resources, or interdisciplinary dynamics that are difficult to quantify.

This study's primary focus on the field of computer science limits the generalizability of the findings across different scientific disciplines. The time period covered in the analysis coincides with significant paradigm shifts within the field, such as the advent of machine learning, deep learning, cloud computing, and blockchain. This period of rapid innovation may amplify the observed role of collaboration and object transitions in ways that might not be mirrored in more stable times or in fields with slower technological evolution. Consequently, these conclusions may not fully apply to other scientific disciplines or eras within computer science itself. The dynamic and highly collaborative nature of computer science, driven by quick technological advances, might differ significantly from the practices of more traditional or less interdisciplinary fields.

To address these limitations, future research could expand the analysis to include various historical periods and other scientific domains. This would help test the robustness and transferability of the current findings and provide insight into how different contextual factors impact the relationship between collaboration, epistemic adjustments, and research interest transitions. Additionally, incorporating more detailed data sources, such as project logs, interviews, or ethnographic studies, could provide a richer understanding of the factors influencing research transitions. The integration of advanced techniques like natural language processing on full-text articles or real-time tracking of project collaborations could further refine the detection of object transitions and better illuminate how intuition and agency evolve during research development.

Another direction worth exploring further is the relationship between epistemic culture and objectual engagement. The way researchers interact with research objects is deeply embedded in the epistemic culture of their field, which includes the norms, values, and practices that shape how knowledge is produced and shared. Future studies could investigate how different epistemic cultures influence the formation and transformation of objectual relationships and how these relationships, in turn, impact researchers' epistemic faculties. In the field of computer science, different objects (such as manifold models, devices, and architectures) are somehow similar to commodities that researchers can select from, giving them relatively high mobility between research objects. However, in other fields, the relationship between researchers and objects can be quite different. The configuration of specific objects deeply influences researchers' activities and can even permeate organizational structures(Knorr-Cetina, 1999). In-depth qualitative or quantitative research that fully considers the characteristics of epistemic culture can greatly enhance our understanding of the processes involved in collective knowledge production. Such studies would offer constructive insights tailored to both individual researchers and research communities.

Data and Code Availability Statement

The datasets generated and analyzed during the current study are publicly available in the Github/Recurrent Collaboration repository, Here.

AI Tools Usage Acknowledgement

This thesis utilized AI tools (ChatGPT) to assist with specific non-critical aspects of the research and writing process. These tools were used for:

Case Understanding (log of interactions here): Assisted in establishing an initial understanding of the case context, including identifying the macro-level problems it aims to solve, existing approaches, and its contributions. Provided inspiration for further in-depth case searching, exploration, and analysis. Primarily applied in Section 3 for case study-related research. The prompt is formatted as follows:

> Now, I will give you a paper. Please read it and based on the content of it, tell me the following:
>
> - What's the relevant landscape of this project? What are the important problem and existing solutions that wirth attentions?
> - What's the contribution of this project? What are the new concepts and/or new connections between concepts that this project offered?

CSO Community Analysis (log of interactions here): Assisted in analyzing, categorizing, and associating CSO lists, providing inspiration and insights for subsequent understanding and analysis of CSO communities. Primarily used in Section 4.2.1 for assessing the classification outcomes of CSO communities and analyzing the results. The prompts is formatted as follows:

> Now I will send you lists of computer science ontologies that belong to the same community. this is a network community division result generated by Louvain algorithm, where the network is the weighted co-appearance network of computer science ontologies on papers. And I need you to reading them and tell me the following:
>
> - What this community of concepts is generally about? Why could it form a relatively united field? Explain the logic or reasoning that these separate ontologies can be clustered together. Give a name to the community.

- What are the important questions and methods in this field?
- Are there external reasons for the clustering of these concepts? Discuss factors such as industrial needs, regularly held competitions, or support from government funding that contribute to clustering these ontologies into a unified field.
- What are significant and representative papers that belong to this field? List 5 to 10 papers that are published after 2010.
- Are there needs or necessities to further split it into subcommunities? Explain the reasons and logic behind whether these concepts should be split into smaller subfields.

LaTeX Usage Guidance and Content Polishing (log of interactions here): Assisted in constructing LaTeX code to create tables, images, and other complex formatting elements to enhance the presentation of the thesis. Provided suggestions for improving sentence fluency and clarity.

The critical intellectual contributions, including the interpretation of findings, formulation of arguments, and development of conclusions, remain entirely the author's work. All outputs from AI tools were critically reviewed, refined, and integrated into the research to support, rather than replace, the scholarly process. The use of these tools has been transparently documented, with conversation logs included for reference. This work adheres to institutional policies on ethical research and academic integrity.

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Appendix

I DBLP-D3 Dataset

DBLP database is an online reference for bibliographic information on major computer science publications (the dblp team, 2022). It is not merely a dynamically updated digital archive but also a searching and navigating tool actively adopted by computer science researchers. Compared to academic databases like OpenAlex, MAG, and WoS, DBLP has a stronger community service orientation. It benefits from continuous, high-frequency human curation, where information on various entries is carefully filtered and verified. Therefore, this dataset is more representative and targeted for research in computer science.

As of January 2024, DBLP indexes over 7 million publications by more than 3.4 million authors. It covers about 55,000 journal volumes, more than 55,000 conference and workshop proceedings, and over 140,000 monographs. DBLP-D3 is a dataset built from the metadata crawled from the DBLP website and combined with external demographic information like Semantc Scholar, CSO, OpenAlex, etc (Wahle et al., 2022). In its most recent update, the data has been maintained through November 2023.

II Computer Science Ontology and Object Engagement

The choice of using the Computer Science Ontology (CSO) for identifying research objects, as opposed to using the Field of Study (FoS) from the Microsoft Academic Graph (MAG)(Färber, 2019) or Semantic Scholar(Ammar et al., 2018; Lo et al., 2020), is technically driven by CSO's higher specificity and focus on the computer science domain. CSO offers a more fine-grained and comprehensive classification system tailored to computer science, capturing nuances and concepts that are more relevant to actual research objects in the field. While FoS provides a broader categorization of disciplines, it lacks the domain-specific detail that is essential for identifying and analyzing the intricate relationships between objects in computer science research. By using CSO, the analysis can more accurately reflect the objects researchers engage with and the shifts in those engagements, thus providing better insights into the dynamics of interest transition within the computer science community.

Our use of CSO was driven by measurement goals. Rather than focusing on which discipline or field a researcher's paper belongs to, we are more concerned with the objects (and objectual wantings) that shape their research interests. At the group level, our focus is on the core-set (Collins, 1981) formed around objects and practices, rather than specialist groups under a disciplines.

The use of CSO offers several key advantages approved by previous studies. Studies have shown that CSO effectively supports topic detection and research trend analysis by offering a fine-tuned categorization of research areas, which is more aligned with actual scientific practices in computer science (Salatino et al., 2021). At the same time, CSO has also performed well in descriptive studies. Researchers have used it to capture more granular aspects of the research process, such as tracing knowledge flow and exchange during the development of NLP (Wahle et al., 2023). Other researchers have used CSO to identify the prerequisite knowledge of knowledge units and link these requests to corresponding textbooks (Nafa et al., 2022). Based on these studies, we have reason to believe that CSO identification is more closely aligned with the actual, dynamic processes in the field of computer science. It accurately reflects the specific objects researchers engage with and the practices they adopt, allowing for more precise descriptions and predictions.

With the help of the CSO identifier, we can input the content of a paper and obtain the CSOs mentioned in it. This study did not perform this process directly but instead matched the D3 dataset with existing identification results. In doing so, we were able to determine the research objects each author engaged with in every project.

III Elaboration on Operationalization and DOE

In this section, I will elaborate on each part of operationalization in detail and, drawing on relevant studies, explain the rationale behind each decision.

Only taking first-author publications into account: In many fields, particularly in computer science, the first author is typically the primary contributor who leads the project, plays a central role in its conceptualization, and is responsible for its execution. Researchers generally attribute the first authorship to the person who made the primary contribution to the project, actively participated in its advancement, and is responsible for the project's outcomes (Fernandes et al., 2021). Authors who are not listed as the first author may not have been involved in the entire research process, and there may not necessarily have been communication or collaboration between them. Previous studies have also implied that, analysis focusing on first-authored papers displays complementary and relative advantages in depicting researchers' contextual and social situation (Kim & Diesner, 2015; Zhai & Yan, 2022).

It must be acknowledged that this approach has some bias due to cultural differences within certain subfields with Computer Science. However, by only examining publications where researchers are listed as the first author, we can ensure as much as possible that the object engagement and collaborative relationships we measure truly exist.

Using a 3-year observation window for object engagement and collaboration: Many previous studies have chosen to track changes in objects on a yearly basis (Foster et al., 2013; Yin, 2024). However, in the field of computer science, significant objectual transitions often require multiple publications over a period of 2 to 3 years to take place. As such, annual analyses struggle to distinguish short-term experiments from long-term explorations. Another common approach is to set time windows. In previous studies, intervals of 2 to 3 years have typically been used as observation periods (Jia et al., 2017; van der Wouden & Youn, 2023; Venturini et al., 2023). In this study, we use a 3-year window for our observations. The use of a 3-year window strikes a balance between capturing medium-term trends in research while avoiding short-term fluctuations that might not reflect true transitions. A window of this length allows for the identification of both sustained interest in certain objects and gradual transitions to new research areas. By comparing adjacent 3-year windows, we can assess how an individual's research evolves in relation to objects and collaborations over time.

Selecting authors with at least three first-authored papers: We selected authors with at least 3 first-authored papers before the observation window for analysis. These scientists typically have a relatively mature research direction and well-formed scholar profile. Generally speaking, after at least three publications, researchers are likely to have developed relatively mature research interests, as well as established patterns in selecting research objects and collaborators.

Comparing differences using Manhattan Distance:

We use the Distance of Object Engagement (DOE) as a measure used to quantify the extent of a researcher's shift in focus on different CSO categories between two time windows: the observation window and the interaction window. DOE is calculated by summing the absolute differences in the number of publications a researcher has contributed to each CSO category in the two windows. The formula for DOE is as follows:

$$DOE = \sum_{i=1}^{n} |P_{i,interaction} - P_{i,observation}| \tag{1}$$

Where:

- $P_{i,interaction}$ is the number of publications in the interaction window that are associated with CSO i,
- $P_{i,observation}$ is the number of publications in the observation window that are associated with CSO i,
- n is the total number of CSO entries.

The values for $P_{i,interaction}$ and $P_{i,observation}$ are calculated using the following formulas:

$$P_{i,interaction} = \sum_{j=1}^{m_{interaction}} \mathbb{I}(i \in CSO_j) \tag{2}$$

$$P_{i,observation} = \sum_{j=1}^{m_{observation}} \mathbb{I}(i \in CSO_j) \tag{3}$$

Where:

- $m_{interaction}$ and $m_{observation}$ represent the total number of publications during the interaction and observation windows, respectively.
- $\mathbb{I}(i \in CSO_j)$ is an indicator function that takes the value of 1 if the j-th publication in a given window contains i in its CSO list, and 0 otherwise.

The DOE captures how much a researcher's engagement with specific research objects (CSOs) has changed between two periods. For example, if a researcher shifts focus from one research object to another, such as from protein analysis to drug development, the decrease in publications related to protein analysis and the increase in publications related to drug development will result in a higher DOE value, indicating a significant transition in research focus. Manhattan Distance (or taxicab distance) is particularly well-suited for this type of analysis because it sums the absolute differences in object engagement across all dimensions. This approach is more straightforward and interpretable when assessing transitions in object engagement, allowing for a clear quantification of the extent to which a researcher's focus on various objects has shifted between observation periods. It provides a direct, meaningful measure of change that reflects the cumulative nature of research engagement.

This measurement differs from previous studies on topic switches which emphasize the proportion of topics (Foster et al., 2013; Jia et al., 2017). I not only take into account the relative frequency of different objects over a given period but also their absolute number of count, as this reflects the intensity of their research activities—essentially, the strength of their interaction with those objects. This is equivalent to many studies that model the interaction between scholars and research objects as a hypergraph and analyze the degree or weights of their connections (Shi et al., 2015; Sourati & Evans, 2022, 2023).

IV CSO Community Construction and Partition

In this study, we constructed a network of relationships between research objects using the Computer Science Ontology (CSO). This network is built based on the frequency with which different CSOs co-appear in academic papers. Each node in the network represents a specific CSO. The edges between these nodes represent the number count of co-occurrence of two

CSOs in the same paper or project. The more frequently two CSOs appear together, the stronger their practical and knowledge-based association, reflecting accumulated knowledge and shared practices. This co-occurrence helps shape tight knowledge communities within the CSO network, signifying areas of intense research focus and collaboration.

The modularity Q is a measure of the strength of the division of the network into communities. It compares the actual density of edges within communities to the expected density of edges if they were distributed randomly. The formula for modularity is as follows:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(C_i, C_j) \tag{4}$$

Where:

- A_{ij} is the weight of the edge between nodes i and j, respectively.
- k_i and k_j are the total degrees (or the sum of the edge weights) of nodes i and j, respectively,
- m is the total number of edges in the network,
- $\delta(C_i, C_j)$ is the Kronecker delta, which is 1 if nodes i and j are in the same community (i.e., $C_i = C_j$) and 0 otherwise.

To identify these closely related communities, we apply the Louvain algorithm for community detection. The Louvain method is a popular algorithm used to partition networks into communities. Given its high efficiency in dealing with large-scale network, it is widely used in social science study (Yin, 2024). The algorithm attempts to maximize the sum of the weights of the edges within a community and minimize the sum of the weights between communities. And the progress is as follows:

- **1. Initialization:** Each node in the network is initially assigned to its own unique community. Therefore, if there are N nodes, there are initially N communities;
- **2. Local Optimization:** The algorithm iterates over each node in the network. For each node i , it evaluates the potential gain in modularity by moving it from its current community to the community of each neighboring node j;
- **3. Community Aggregation:** After all nodes have been assigned to their new communities (if a move was beneficial), each community is collapsed into a single super-node. The weight of the edges between super-nodes represents the sum of the edge weights between nodes in the original communities;

- **4. Repetition:** Steps 2 and 3 are repeated iteratively on the new network formed by the super-nodes until no further modularity gain can be achieved.

- **5. Termination:** The algorithm terminates when no more modularity gain is possible. At this point, the optimal division of the network into communities has been found.

In the network we constructed, consisting of 10,786 nodes (representing CSOs) and 5,841,680 edges (co-occurrence links between CSOs), the Louvain algorithm is applied in two rounds of community detection, dividing the network into 65 communities of varying sizes. The goal is to ensure that the communities are well-defined, with strong internal connectivity. The Q value resulting from this division is 0.42, which indicates a moderately strong community structure. A Q value between 0.3 and 0.7 suggests meaningful and well-defined groupings, meaning the CSOs within the same community are more closely linked to each other than to those in other communities, which makes the detected communities coherent and distinct in the network.

This analysis provides insight into how research objects (CSOs) are clustered in the research field and helps identify key areas of focus and their relationships within the computer science community.

V Objects' Community Affiliation and Researchers' DCA

Here's a detailed explanation with the corresponding formula for calculating each object's community affiliation and the researcher's Distance of Community Affiliation (DCA):

Each object (CSO) is represented as a community affiliation vector V_{object} , where the vector has dimensions corresponding to the number of detected communities k . For each object, $V_{\text{object}} = (v_1, v_2, \ldots, v_k)$, where each component v_i indicates the proportion of the object's co-occurrence with other objects in community i . The sum of all components in the vector is normalized to 1:$\sum_{i=1}^{k} v_i = 1$.

For each researcher, we aggregate the affiliation vectors of all objects they engage with in a specific time window (observation or interaction). The community affiliation vector for a researcher R during a given time window is calculated as the weighted sum of the vectors of all objects O_j the researcher has worked on, where the weight corresponds to the number of publications involving that object P_j:

$$V_{\text{researcher}} = \frac{\sum_{j=1}^{n} P_j \cdot V_{\text{object}j}}{\sum_{j=1}^{n} P_j} \tag{5}$$

Here, n represents the total number of objects the researcher engaged with during the time window.

The DCA (Distance of Community Affiliation) between two time windows (e.g., observation window and interaction window) is then calculated as the Manhattan Distance between the researcher's affiliation vectors from the two windows. If V_{obs} is the vector for the observation window and V_{int} is the vector for the interaction window, the DCA is calculated as:

$$\text{DCA} = \sum_{i=1}^{k} |V_{\text{obs},i} - V_{\text{int},i}| \tag{6}$$

This formula measures the total change in community affiliation between the two time periods. A higher DCA value indicates a more significant shift in the researcher's focus on different community-affiliated objects, reflecting a more substantial epistemic transition. Conversely, a lower DCA implies more continuity and stability in the researcher's object engagements across time, even though they may have actually undergone significant objectual transitions. This is because transitions between objects within the same or similar community affiliations may not register as a high DCA, despite potentially involving substantial changes in research focus or methodologies. Thus, DCA specifically captures the degree of epistemic distance between the communities, rather than the magnitude of the objectual shift itself.

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