Why perspective matters?
On the quest of computational human-centered metascience

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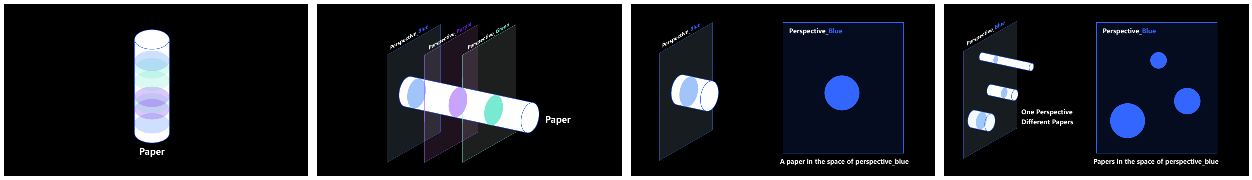
Abstract

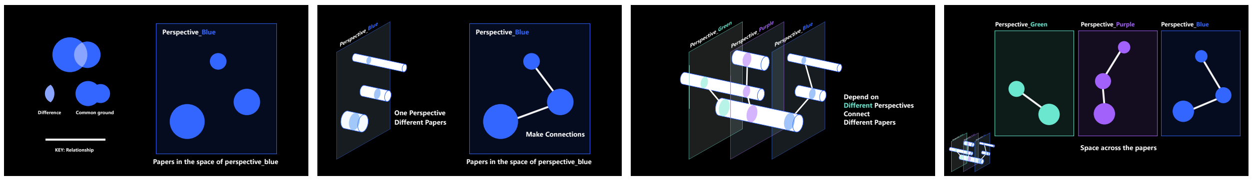
Metascience helps improve scientific research by not only synthesizing research on a topic but also elaborating the common sense for shaping an appropriate mindset to study the topic. Though the end-users of metascience are scientists, user-centered considerations have been under-researched. Modeling how scientists work with science is possible, given the great progress on computational modeling of human cognitive progress. Hence, some major obstacles for scientists, *i.e.*, proposing perspectives and hypotheses, or capturing global information and local details simultaneously, can be partly automated and transparentized, improving the reliability and reproducibility of research. This concept paper introduces computational human-centered metascience through the most elementary research skill—framing a perspective with reviewing the literature. This problem can be decomposed to computational, algorithmic, and implementational levels, regarding the macro view how perspective communicate with each other, how to frame perspectives automatically, and how to scientists understand and present perspectives. This case on perspective modeling goes over the major components to consider human-centered metascience. On this basis, such introspective understanding can be generalized to identify different mindsets of scientific research. We further review the divergence of perspectives and the convergence of common grounds in the development of science to enhance the value of introspective studies.

Metascience helps improve the sciences through studying and optimizing scientific research (Ioannidis et al., 2015). As metascience provides *a bird's eye view of science*, reviews serve as the bird's wing (Ioannidis, 2022)—(1) for researchers, a good review frames a specific perspective out of the literature with the authors' unique insights about the topic; (2) for the community, reviews communicate between groups of researchers with different mindsets. However, the merits of reviews limited by an elementary contradiction—on the prerequisite of naturalism (Papineau, 2021), the end-user of science is human, while science aims to describe the world. That is, people work with science from diverse specific perspectives, but the world described by science is the one. Hence, a good review for research synthesis (Gurevitch et al., 2018), should cover the perspectives on the same topic. Further, it should also cover the *common sense*, *e.g.*, methodologies, for studying the topic, in order to really be helpful to the community. These shape the *human-centered* feature of reviews. Unfortunately, the value of studying these interactions between science and scientists is often underestimated. Can we compute the perspective and the common sense? Philosophers have gave the initial responses through the introspection from scientists, *i.e.*, Peirce's Abduction and Popper's Hypothetico-deduction (Peirce, 1955; Popper, 1959), providing us with a good starting point to answer the questions in a computational way—as the significant progress in computational cognitive science (Lake et al., 2017), we are close to be able to model complex thinking patterns in real scenes. Computational models of scientific thinking patterns may lead to two potential merits: (1) proposing and predicting research common sense given specific research context (*e.g.*, experiments, data, and literature); and (2) providing strong evidence at the large scale to current debates on the appropriateness of methodologies. Of course modeling scientific thinking patterns would never replace the insights generated by researchers—it is only generating proposals to broaden the limited bandwidth of researchers, and researchers refer to the proposals according to their values. This also disentangles researchers' personal bias from the entire development of the research projects, thus improve the reliability and reproducibility of science by transparentizing the decisions made by researchers.

Given the background, we propose to study *computational human-centered metascience* in two levels: (1) perspective-driven narrative and systematic literature mining; (2) introspective scientific thinking pattern modeling. Specifically, the former is an indispensable basis for the latter, which makes the computational modeling work much more accessible. We can explicitly model a perspective, whether predefined or generated, then project the literature to this perspective, framing an expert review with high-level insights, a systematic review with research methodologies, and a meta-analysis



(a) a paper with rich content (b) slices as multiple perspectives (c) projection to a slice (d) a frame from a set of papers



(e) relations between slices (f) a graph framing a perspective (g) frames like parallel spaces (h) diverse perspective frames

Figure 1: **Framing diverse perspectives from the literature**

with result synthesis from the literature, only conditioned on what kind of perspective it is (see Fig. 1 for details). This computational pipeline automates (1) framing ideas from researchers' perspectives; (2) aligning researchers' mindsets to understand each other; and (3) merging diverse perspectives to develop a complete and deep understanding. On this basis, we are able to handle in-situ scientific problems in the human-centered way given the model from the literature.

Perspective matters in science

Why does perspective matter? Everyone answers from her own perspective—this may have already shown the significance of perspective itself. People view the world conditioned on perspectives due to highly limited cognitive resources (Lieder and Griffiths, 2020); and people *interpret* the world from different perspectives based on diverse *prior*—especially when the world is a very complex system with connected concepts, whether it is consist of empirical thoughts or of scientific theories and explanations (Gopnik and Wellman, 1994)—that is why good research is framing a perspective, covering a wide range from result collection to theory comprehension (Abend, 2008; Denyer and Tranfield, 2009); and may also explain how our diverse communities of sciences have become what they are today, with inclusion of the known unknowns (*e.g.*, evidence-based medicine (Sackett, 1997)), diverse competing theories (Ioannidis, 2005), and active interdisciplinary collaborations (Bronstein, 2003).

The first thing is to identify the scales of the problem. Here we propose three levels of the scientific problem behind human-centered metascience according to Marr's levels of analysis theory (Marr, 1982). Marr's paradigm provides researchers with a framework to analyze a problem in three levels: (1) *computational level* defines the objective of an abstract computational problem, *i.e.*, *what is the problem to solve*; (2) *algorithmic level* indicates the algorithm and the transformation of representation to be performed for solving the problem, *i.e.*, *how to solve the problem*; and (3) *implementational level* focuses on the physical basis to implement the algorithm, *i.e.*, *how to realize the solution*.

Analogously, for human-centered metascience, we have (1) *computational level*: the macro abstract formulation of framing and communicating perspective frames; (2) *algorithmic level*: the explicit modeling of perspectives and the automated computational pipeline for mining perspectives from the literature; and (3) *implementational level*: the interaction between science and researchers, the end-user of science, such as user-friendly interface of reviews.

Computational level The computational level of human-centered metascience can be analogous to a distributed Bayesian inference problem (Ellison, 2004; Krafft et al., 2016) (see Tab. 1 for details). First, a researcher cannot know everything about a piece of high-dimensional knowledge due to limited cognitive resources (Lieder and Griffiths, 2020). This is in line with *the curse of dimensionality* in density estimation—let $P(x)$ be the marginal density that knowledge $x \in \mathcal{X}$ ($\mathcal{X}$ is the high-dimensional space of all modalities of knowledge), estimating $P(x)$ directly is intractable. Second, researchers have diverse mindsets due to expertise, experience, background, and interest. We can view the mindsets as prior z in latent space $\mathcal{Z}$ with all potential perspectives, where $P(z)$ is the distribution of the perspectives. Third, the

Table 1: **The analogy between computational level of human-centered metascience and distributed Bayesian inference.**

	challenge	prior	generation	merge
Bayesian inference	intractable $P(x)$	$P(z) \in \mathcal{Z}$	$P(x,z) = P(z)P(x \mid z)$	$P(x) = \sum_z P(x,z)$
computational level	limited bandwidth	diverse prior	diverse interpretations	in-depth understanding

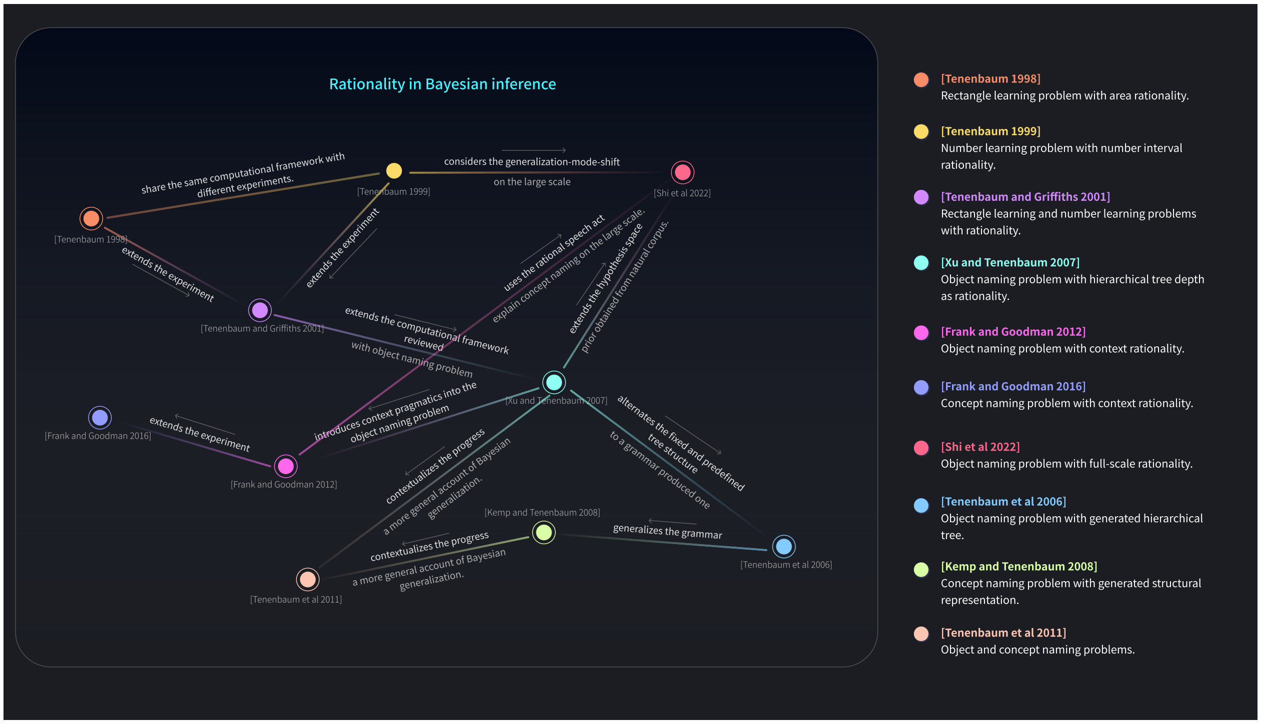


Figure 2: **An example for visualizing the Bayesian generalization literature from the perspective of *Rationality*.** The perspective frame is visualized by Shi and Zhu (2022), a tool for generating frames of perspectives in scientific research

human-centered knowledge can be viewed as the joint density $P(x, z)$, which can be generated through $P(z)P(x|z)$ according to Bayes theorem, where $P(x|z)$ the interpretation of knowledge x conditioned on perspective z. Finally, if the diversity of the researchers is enough and we are able to merge the perspectives, we obtain a deeper understanding of the piece of knowledge. Formally, merging perspectives is the marginalization over $P(x, z)$, *i.e.*, $P(x) = \sum_z P(x, z)$. In contrast to research synthesis, we explicitly model the process of generating, interpreting, and merging. To note, this formulation views knowledge in a static way—if we append a temporal dimension to view science as a dynamic process, we may be able to study the evolution of science by integrating the propagation of perspectives into the graph-dynamics based science of science research as a constraint (Griffiths, 2020; Fortunato et al., 2018).

Algorithmic level The algorithmic level of human-centered metascience aims to automate the process of generating, interpreting, and merge. In contrast to current review composition techniques, which mostly combine the general summarizations of multiple papers (Wallace et al., 2021; DeYoung et al., 2021), the algorithm generates summarizations of papers and identify the latent relations between studies conditioned on the given perspective. To help understand the input and the output of the algorithmic level problem, we use extremely simple geometries to illustrate the abstract concepts about perspective. If we treat a paper as a three-dimensional cylinder, the potential perspectives in the paper can be an infinite series of slices. In general, a good paper is rich enough to be viewed from diverse perspectives (see Fig. 1a). For example, we may focus on its hypotheses and results, methods, experimental paradigms—anything that may support our claim. Interpreting a paper from a specific perspective is projecting the three-dimensional entity to a specific two-dimensional slice (see Fig. 1b and 1c). A perspective is a two-dimensional space, which is typically called a frame of the perspective, where different slices of different paper connect with each other via their relations conditioned on the perspective (see Fig. 1d to 1f). Please note that we are not interested in the general relation between two papers, such as A being cited by B—we are interested in the latent relation only given the perspective, for example, A and B are mutually equivalent in the essence of problem formulation, A advances by B regarding computational efficiency. If A and B share similar backgrounds given the perspective, the relation between A and B may likely be the difference; if not so, the relation may likely be the common (see Frank and Goodman (2012) for the descriptions about the phenomenon). Since people are diverse enough in expertise, background, and interest, to come up with diverse perspectives, there can be infinite perspective frames for across an arbitrary set of papers, just like infinite parallel spaces in the universe as we imagined—papers are the same, yet interpretations become different (see Fig. 1g and 1h). Hence, this computational pipeline has the potential to help scientists come up with mutually exclusive and collectively exhaustive proposals of perspectives and help find out latent relations between studies (see Fig. 3a). This makes the automated process of proposing insights from the literature much more transparent, reliable, and controllable. A review reconstruction task is also designed to evaluate the pipeline—the interpretations of citing papers from well-written narrative reviews and systematic reviews are collected as ground-truths (see Fig. 3b)—on the assumption that the collected reviews are i.i.d. to the entire literature.

(a) pipeline for perspective-oriented literature mining (b) review reconstruction as the pipeline evaluation process

Figure 3: **The computational pipeline in the algorithmic level problem of human-centered metascience**

Implementational level The implementational level of human-centered metascience studies the interaction between science and scientists. Scientists, whether senior researchers as lab directors or junior students under training, are very creative but suffering from limited cognitive bandwidth (Griffiths, 2020). Meanwhile, computers are never as generalizable as scientists, but have much larger memory bandwidth. Hence, appropriate knowledge representations of science that facilitate the creativity and makeup the bandwidth are crucial for human-centered considerations. In contrast to scientific literature visualization, the canonical content-centered approach where the all-in-one knowledge representation is designed for the general users (Li et al., 2019), the human-centered approach should generate simplified individual proposals of knowledge representation (*e.g.*, visualization of systematic reviews) to different users according to their perspective. Specifically, the three classical families of knowledge organization protocol, hierarchical structure (tree), many-to-many mapping (label), and multi-layer network (graph), trade-off between accessibility and expressivity (see Tab. 2 for details). From the content-centered view, the expressivity of label outperforms tree because the division space is extended from single to multiple; and that of graph outperforms label because the explicit knowledge integration of first-order relation. From the human-centered view, the user accessibility comes in the opposite trend because if one wants to frame a perspective with a graph, she must already have been come up with insights about the knowledge, and tree and label are more accessible as a quick review or intuitive, instant, and superficial understanding of the knowledge. These families of protocol should automatically adapt to different scenarios and users, *e.g.*, physicians at evidence-based medical decision or cross-disciplinary researchers searching in a novel domain without their expertise. Rigorous behavioral studies should also be carried out to study the effect of these treatments on science education through the A/B test (Angrist et al., 1996).

Table 2: **The trade-off between expressivity and accessibility over the three families of knowledge organization protocols.** Multiple-space: multiple division spaces, such as the space of model, the space of result, the space of motivation, *etc*. Multiple-entry: more than one entry, and the root is the only one entry in a tree. First-order relation: relation between two entities. Rough clustering: classify entities without knowing their pairwise relations. Quick labeling: classify entities in a non-parametric way, *i.e.*, without the preregistration of the categorical spaces. Meaningless entry: structural constraints without explicit semantic meaning.

content- or human-centered	expressivity			accessibility		
features	multiple-space	multiple-entry	first-order relation	rough clustering	quick labeling	meaningless entry
hierarchical structure (tree)	✗	✗	✗	✓	✓	✓
many-to-many mapping (label)	✓	✓	✗	✓	✓	✗
multi-layer network (graph)	✓	✓	✓	✗	✗	✗

Introspective study on scientific thinking patterns

Usually there is no general methodology that can serve as *the gold standard* for all specific domains in the sciences—there is no free lunch in the world, and every domain has its own *common sense* emerged as the result of the hard work by generations of scientists. The common sense can be high-level thinking patterns for identifying scientific problems, insights for making plausible hypotheses, principles for designing experiments, and methodologies for explaining observations; and also low-level working techniques, bag-of-tricks, and specific systems of terminologies. The diverse specific domains in the sciences may distinct from each other by composing these components with different weights, which is generally accepted as *the philosophy of the domain*. Domain-specific common sense is priceless for the sciences, and its value has long been underestimated. Though the data mining for science community, such as artificial-intelligence-aided drug design, has enjoyed a great progress over recent years (Schneider et al., 2020), only a small amount of cases and domain knowledge has been exploited in computation (Dai et al., 2021). Usually the design of computation models are tricky because the computational problem has been abstracted to a pure data mining problem without any need of domain expertise. The elementary problem is that this kind of algorithms can only generate or predict things they have seen in the data. Machines cannot help people imagine. Hence, introspectively modeling the thinking patterns of scientists may help researchers go beyond *current progress in the domain* to imagine the future.

Discovery *vs*. Invention Some domains of science are observation-explanation-dominant, such as experimental chemistry, developmental psychology, economics, and history—the main driving force of these domains is *understanding something*, where problems and hypotheses are more important than results, and the expectation for discovery is much more higher than that for invention; other domains of science are requirement-goal-dominant, such as computer engineering, robotics, finance, and management—the main driving force of theses domains is *realizing something*, where the expectation for invention is much more higher than that for discovery. Besides these two families, some domains communicate between discovery and invention, such as drug design, energy materials (battery) research, and computational sciences. These domains iteratively switch between discovery and invention—sometimes a requirement-driven invention leads to a series of property discovery based on the invention; and sometimes a significant discovery leads to insights on a great invention. A famous example in computation is the invention of the imagined number—it is invented for solving cubic equations, but more properties have been discovered subsequently to form the domain of complex analysis. And for domains like drug design and battery design, explaining the working mechanism of an invented structure is crucial for guaranteeing the reliability of the target product. This research methodology comes from another great effort—since there is no principles help design the structure directly as a production of rules, we design the structures from intuition, then explain the mechanisms as constraints over a symbolic production system. Such rational decision is the hallmark of human intelligence, which should be explicitly modeled to improve research.

Human-centered *vs*. Content-centered As aforementioned, the contradiction between human-centered and content-centered way is elementary in science. Has any domain balance the description of the world and satisfying human need? The answer is yes. As a basic tool for computation, programming languages communicates between human users and the world—(1) a programming language is used to describe or model an object, a scenario, or a system, *e.g.*, 3D masks of human faces, biological experiment protocols, and electronic systems; (2) a programming language is designed to satisfy users' need and bias, such as the requirements for object-oriented programming, for functions, and for stream and procedures (Abelson and Sussman, 1996). The former comes as low-level instruction sets that only consider content modeling, while the latter comes as high-level programming languages that only consider user requirement, assuming that all programming languages can be translated to instructions. And the compiler bridges the two ends. Hence in science, we may also need such compilers that translate human-centered perspectives toward a mediator that can be merged with or be translated to other perspectives. The compilers should capture how the perspective is framed from the content. And the mediator is a commonground that reaches the consensus between different perspectives. Human-centered metascience is not isolating the human-centered and the content-centered views—on the contrary, it is explicitly considering the communication between the two fashions to mitigate the contradiction.

Perspective *vs*. Commonground If a personal perspective is a conditional view of the world, a commonground should be the consensus reached by a group of persons without conditioning. In the extreme situations, if the group of consensus is large enough to include all people in the world, the commonground hold by the group becomes the commonsense. Here we hypothesize that perspective and commonsense should be the two ends of the entire knowledge space, between which are different levels of commongrounds, different in levels according to group sizes (see Fig. 4). Knowledge close to perspective is in-depth, narrow, and diverse across population; knowledge close to commonsense is shallow, general, and convergent over population. Going from perspective (lower levels of commonground) to commonsense (high levels of commonground) is reducing knowledge to their more basic and abstract forms, washing off condition-specific considerations and human bias; going from higher to lower levels of commonground is interpreting knowledge according to their bias and other constraints. This may echo the finding that semantic representations of abstract words are more diverse than that of concrete words (Wang and Bi, 2021)—compared with concrete words, the abstract ones have 'a longer way' to be grounded, which means more choices for the interpretation. Similarly, given the great diversity of the science community, we must admit that personal bias may lead to scientific flaws, but some of them become the starting points of great breakthroughs in the history of science, since they are from numerous thinking based on both expertise and insight, such as the discovery of Kekule structure (Gruber, 1981). Kekule's perspective on organic chemistry comes from strong personal bias. Hence, we should rethink the value of diversity—instead of trying to eliminate all bias in science, we can try embracing the bias that can be subsequently framed into perspectives which

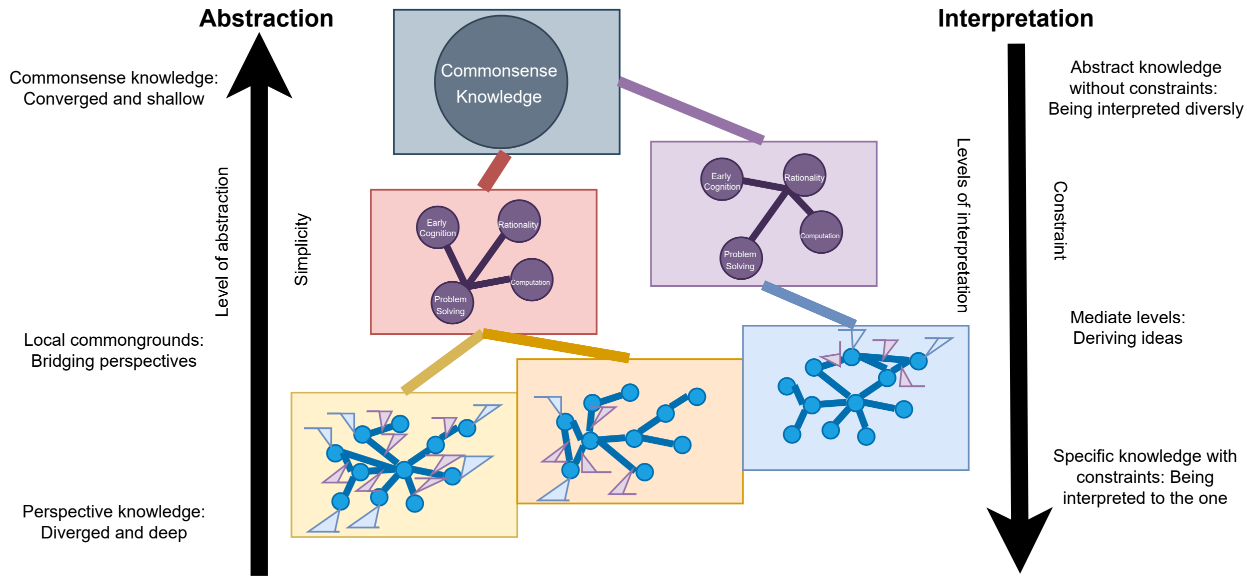


Figure 4: **Illustration of perspective and commonsense as two ends of human scientific knowledge**

lead to meaningful research directions. After all, although commongrounds bridge the obstacles between sciences for communication and learning, it is perspective that extends the boundary of science, from the deep and narrow.

Abduction *vs*. Hypothetico-deduction Based on the hypothesis of knowledge space between perspective and commonsense, we are facing a crucial problem: How do the commongrounds emerge? This is a typical *chicken-and-egg problem*. After all, whether does the discovery or the invention come first? More concretely, in specific domains of science, is a commonground more likely derived from its higher-level commonground (commonsense) in a top-down way, or from its lower-level commonground (perspective) in a bottom-up way? Both happens. When discovery is coming from *the observation of surprising facts*, it reduces the explanation to higher levels of commongrounds successively (van Riel and van Gulick, 2019); when invention is coming from *the motivation for unrealized goals*, it preregisters a target level of commonground at first and rationalize the pathway (Cushman, 2020). This explanation connects discovery and invention with Abduction and Hypothetico-deduction respectively. In the two frameworks, not only the reasoning is nondeterministic, but the prior model crucially determines the direction of reasoning. Hence, these two thinking patterns are highly human-centered. Moreover, as Peirce has reiterated, *Abduction is the only logical operation which introduces any new idea; it encompasses all the operations by which theories and conceptions are engendered* (Peirce, 1955), we are able to believe that Abduction and Hypothetico-deduction are two of the most significant scientific thinking patterns that have the potential to integrate individual perspectives and to derive domain-specific common sense. Once we are able to go beyond scientific data mining, we can build a machine scientist that help imagine the future of science.

Table 3: **The connections between the discovery-driven and invention-driven research, with respective to the two scientific thinking frameworks, Abduction and Hypothetico-deduction.**

	Abduction (discovery)	Hypothetico-deduction (invention)
input	**observations** inconsistent with current knowledge	**requirements** that cannot be realized with current knowledge
objective	reduce the explanatory hypotheses form the observation	rationalize the hypothesized derivations for the target
output	the **plausible explanation** of the observation	the **rationalized realization** of the requirement
example	the discovery of Kepler's laws of planetary motion	the invention of the imagined number

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