A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

I. Pérez-Messina*, D. Ceneda*, M. El-Assady**, S. Miksch* and F. Sperrle***

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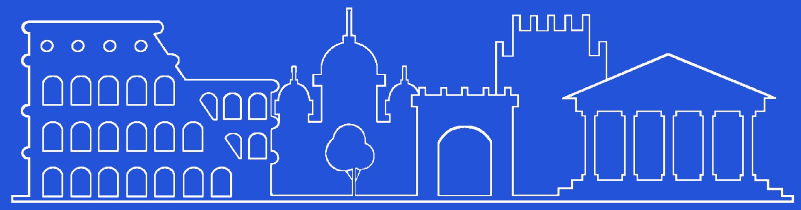

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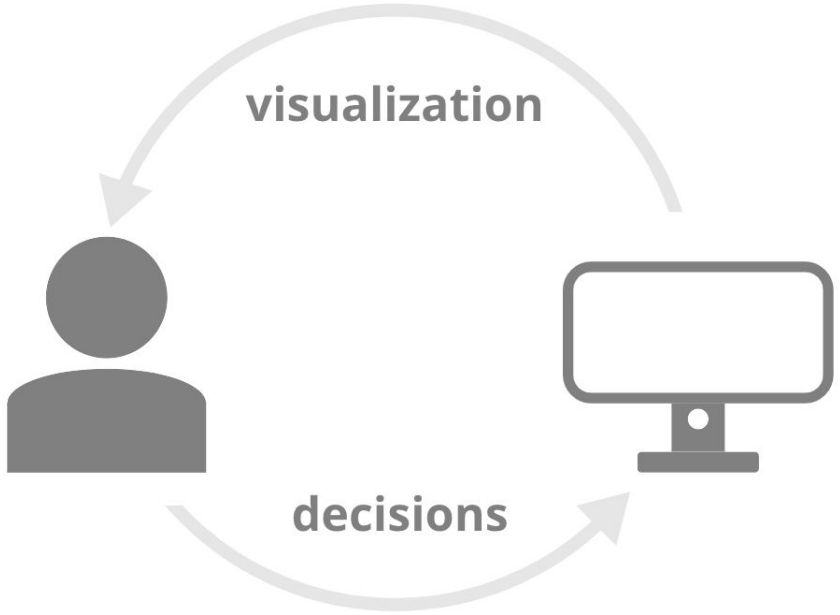
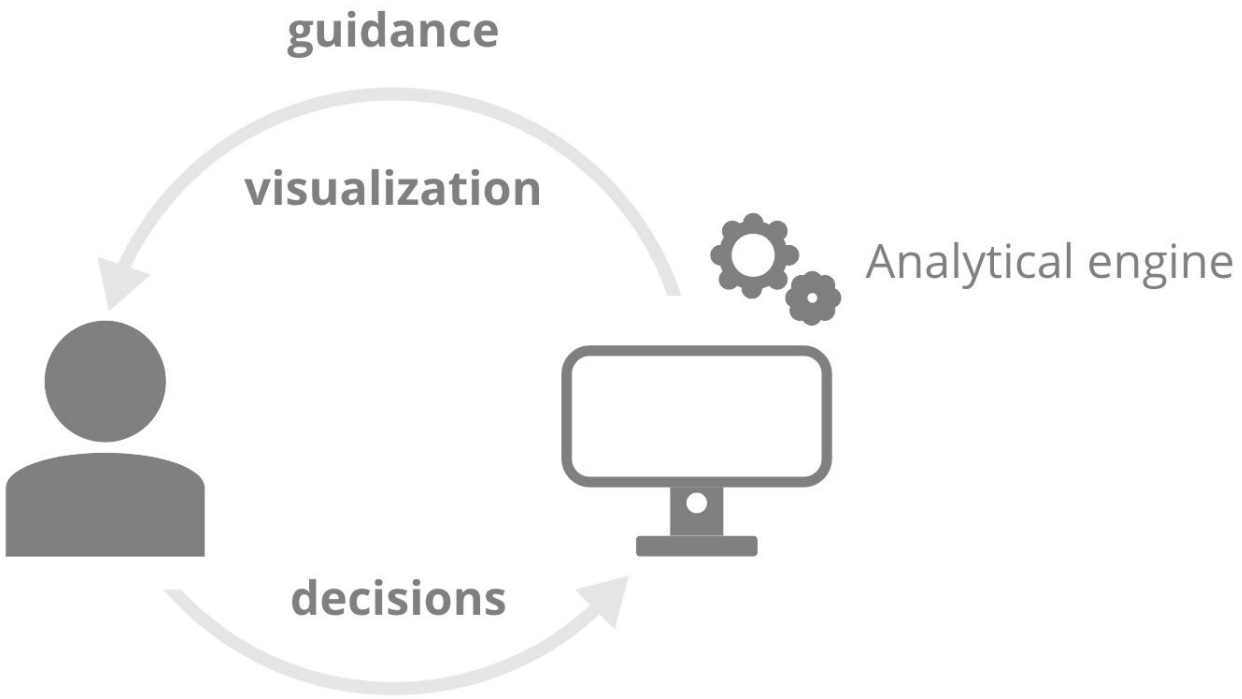
Guidance

User-initiative VA



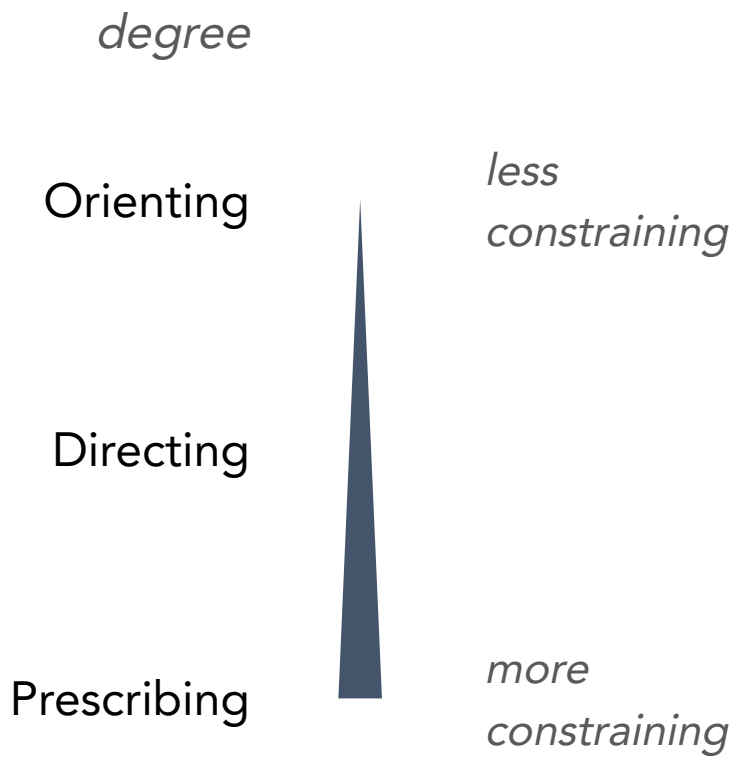
Guidance

Mixed-initiative VA



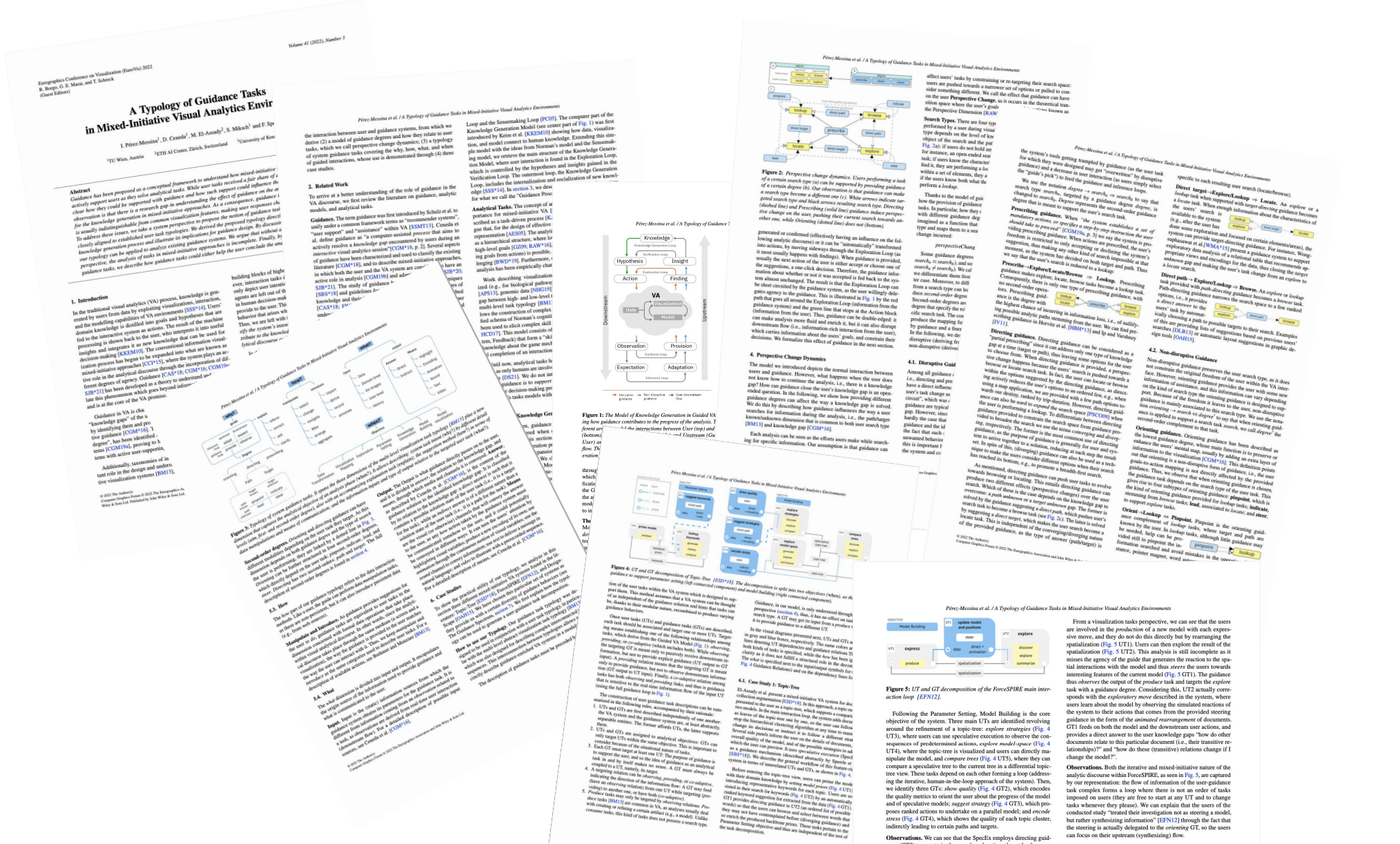
Guidance Degrees

Guidance degrees are defined by the constraint they impose on user action



Ceneda, D., Gschwandtner, T., May, T., Miksch, S., Schulz, H. J., Streit, M., & Tominski, C. (2016). **Characterizing guidance in visual analytics**. *IEEE transactions on visualization and computer graphics*, *23*(1), 111-120.

Guidance Degrees

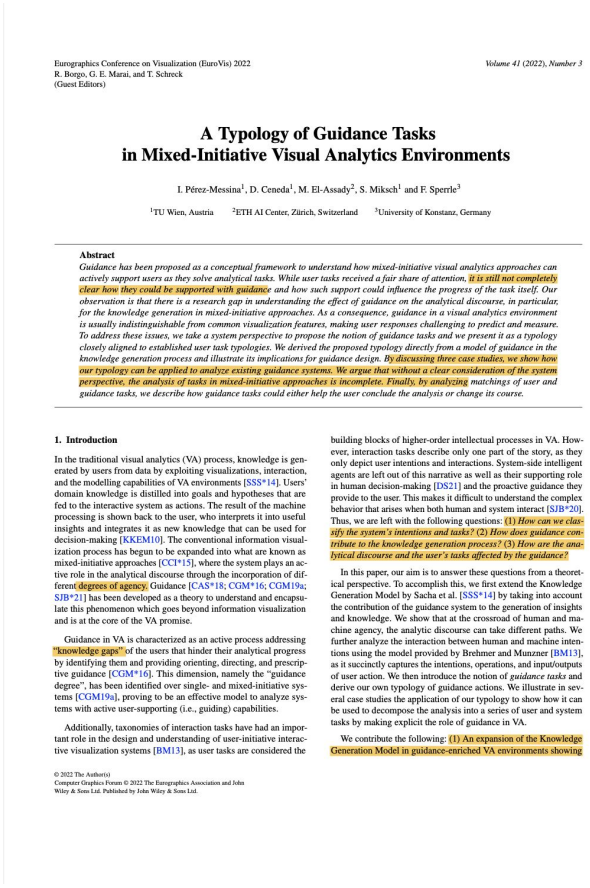


Guidance Degrees

Orienting guidance

Used to preserve or enhance the users' mental map

Does not constrain user action



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Abstract

Guidance has been proposed as a conceptual framework to understand how mixed-initiative visual analytics approaches can actively support users as they solve analytical tasks. While user tasks received a fair share of attention, it is still not completely clear how they could be supported with guidance and how such support could influence the progress of the task itself. Our observation is that there is a research gap in understanding the effect of guidance on the analytical discourse, in particular, for the knowledge generation in mixed-initiative approaches. As a consequence, guidance in a visual analytics environment is usually indistinguishable from common visualization features, making user responses challenging to predict and measure. To address these issues, we take a system perspective to propose the notion of guidance tasks and we present it as a typology closely aligned to established user task typologies. We derived the proposed typology directly from a model of guidance in the knowledge generation process and illustrate its implications for guidance design. By discussing three case studies, we show how our typology can be applied to analyze existing guidance systems. We argue that without a clear consideration of the system perspective, the analysis of tasks in mixed-initiative approaches is incomplete. Finally, by analyzing matchings of user and guidance tasks, we describe how guidance tasks could either help the user conclude the analysis or change its course.

1. Introduction

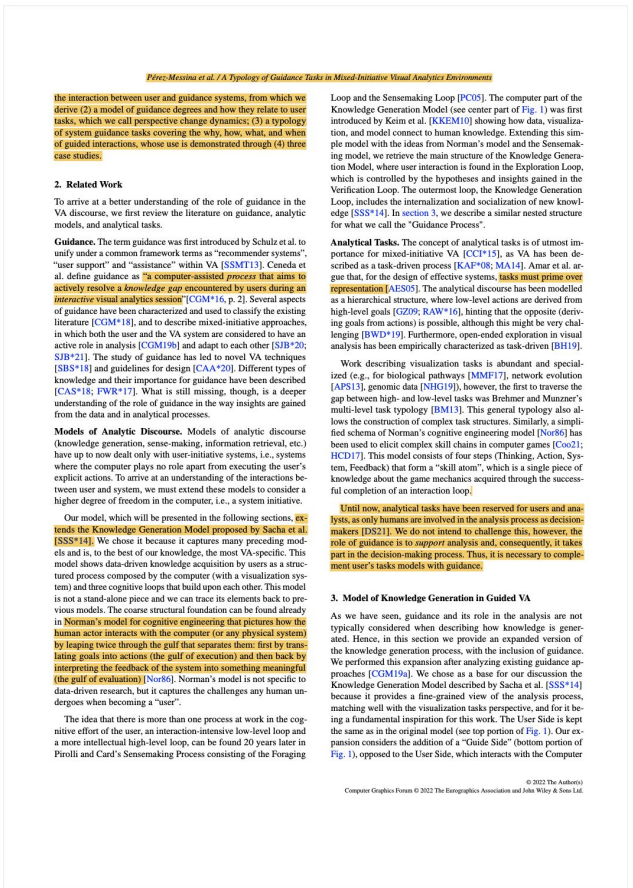
In the traditional visual analytics (VA) process, knowledge is generated by users from data by exploiting visualizations, interaction, and the modelling capabilities of VA environments [SSS*14]. Users' domain knowledge is distilled into goals and hypotheses that are fed to the interactive system as actions. The result of the machine processing is shown back to the user, who interprets it into useful insights and integrates it as new knowledge that can be used for decision-making [KKEM10]. The conventional information visualization process has begun to be expanded into what are known as mixed-initiative approaches [CCI*15], where the system plays an active role in the analytical discourse through the incorporation of different degrees of agency. Guidance [CAS*18; CGM*16; CGM19a; SJB*21] has been developed as a theory to understand and encapsulate this phenomenon which goes beyond information visualization and is at the core of the VA promise.

Guidance in VA is characterized as an active process addressing "knowledge gaps" of the users that hinder their analytical progress by identifying them and providing orienting, directing, and prescriptive guidance [CGM*16]. This dimension, namely the "guidance degree", has been identified over single- and mixed-initiative systems [CGM19a], proving to be an effective model to analyze systems with active user-supporting (i.e., guiding) capabilities.

Additionally, taxonomies of interaction tasks have had an important role in the design and understanding of user-initiative interactive visualization systems [BM13], as user tasks are considered the building blocks of higher-order intellectual processes in VA. However, interaction tasks describe only one part of the story, as they only depict user intentions and interactions. System-side intelligent agents are left out of this narrative as well as their supporting role in human decision-making [DS21] and the proactive guidance they provide to the user. This makes it difficult to understand the complex behavior that arises when both human and system interact [SJB*20]. Thus, we are left with the following questions: (1) *How can we classify the system's intentions and tasks?* (2) *How does guidance contribute to the knowledge generation process?* (3) *How are the analytical discourse and the user's tasks affected by the guidance?*

In this paper, our aim is to answer these questions from a theoretical perspective. To accomplish this, we first extend the Knowledge Generation Model by Sacha et al. [SSS*14] by taking into account the contribution of the guidance system to the generation of insights and knowledge. We show that at the crossroad of human and machine agency, the analytic discourse can take different paths. We further analyze the interaction between human and machine intentions using the model provided by Brehmer and Munzner [BM13], as it succinctly captures the intentions, operations, and input/outputs of user action. We then introduce the notion of *guidance tasks* and derive our own typology of guidance actions. We illustrate in several case studies the application of our typology to show how it can be used to decompose the analysis into a series of user and system tasks by making explicit the role of guidance in VA.

We contribute the following: (1) An expansion of the Knowledge Generation Model in guidance-enriched VA environments showing



the interaction between user and guidance systems, from which we derive (2) a model of guidance degrees and how they relate to user tasks, which we call perspective change dynamics; (3) a typology of system guidance tasks covering the why, how, what, and when of guided interactions, whose use is demonstrated through (4) three case studies.

2. Related Work

To arrive at a better understanding of the role of guidance in the VA discourse, we first review the literature on guidance, analytic models, and analytical tasks.

Guidance. The term guidance was first introduced by Schulz et al. to unify under a common framework terms as "recommender systems", "user support" and "assistance" within VA [SSMT13]. Ceneda et al. define guidance as "a computer-assisted *process* that aims to actively resolve a *knowledge gap* encountered by users during an *interactive* visual analytics session"[CGM*16, p. 2]. Several aspects of guidance have been characterized and used to classify the existing literature [CGM*18], and to describe mixed-initiative approaches, in which both the user and the VA system are considered to have an active role in analysis [CGM19b] and adapt to each other [SJB*20; SJB*21]. The study of guidance has led to novel VA techniques [SBS*18] and guidelines for design [CAA*20]. Different types of knowledge and their importance for guidance have been described [CAS*18; FWR*17]. What is still missing, though, is a deeper understanding of the role of guidance in the way insights are gained from the data and in analytical processes.

Models of Analytic Discourse. Models of analytic discourse (knowledge generation, sense-making, information retrieval, etc.) have up to now dealt only with user-initiative systems, i.e., systems where the computer plays no role apart from executing the user's explicit actions. To arrive at an understanding of the interactions between user and system, we must extend these models to consider a higher degree of freedom in the computer, i.e., a system initiative.

Our model, which will be presented in the following sections, extends the Knowledge Generation Model proposed by Sacha et al. [SSS*14]. We chose it because it captures many preceding models and is, to the best of our knowledge, the most VA-specific. This model shows data-driven knowledge acquisition by users as a structured process composed by the computer (with a visualization system) and three cognitive loops that build upon each other. This model is not a stand-alone piece and we can trace its elements back to previous models. The coarse structural foundation can be found already in Norman's model for cognitive engineering that pictures how the human actor interacts with the computer (or any physical system) by leaping twice through the gulf that separates them: first by translating goals into actions (the gulf of execution) and then back by interpreting the feedback of the system into something meaningful (the gulf of evaluation) [Nor86]. Norman's model is not specific to data-driven research, but it captures the challenges any human undergoes when becoming a "user".

The idea that there is more than one process at work in the cognitive effort of the user, an interaction-intensive low-level loop and a more intellectual high-level loop, can be found 20 years later in Pirolli and Card's Sensemaking Process consisting of the Foraging Loop and the Sensemaking Loop [PC05]. The computer part of the Knowledge Generation Model (see center part of Fig. 1) was first introduced by Keim et al. [KKEM10] showing how data, visualization, and model connect to human knowledge. Extending this simple model with the ideas from Norman's model and the Sensemaking model, we retrieve the main structure of the Knowledge Generation Model, where user interaction is found in the Exploration Loop, which is controlled by the hypotheses and insights gained in the Verification Loop. The outermost loop, the Knowledge Generation Loop, includes the internalization and socialization of new knowledge [SSS*14]. In section 3, we describe a similar nested structure for what we call the "Guidance Process".

Analytical Tasks. The concept of analytical tasks is of utmost importance for mixed-initiative VA [CCI*15], as VA has been described as a task-driven process [KAP*08; MA14]. Amar et al. argue that, for the design of effective systems, tasks must prime over representation [AES05]. The analytical discourse has been modelled as a hierarchical structure, where low-level actions are derived from high-level goals [GZ09; RAW*16], hinting that the opposite (deriving goals from actions) is possible, although this might be very challenging [BWD*19]. Furthermore, open-ended exploration in visual analysis has been empirically characterized as task-driven [BH19].

Work describing visualization tasks is abundant and specialized (e.g., for biological pathways [MMF17], network evolution [APS13], genomic data [NHG19]), however, the first to traverse the gap between high- and low-level tasks was Brehmer and Munzner's multi-level task typology [BM13]. This general typology also allows the construction of complex task structures. Similarly, a simplified schema of Norman's cognitive engineering model [Nor86] has been used to elicit complex skill chains in computer games [Coo21; HCD17]. This model consists of four steps (Thinking, Action, System, Feedback) that form a "skill atom", which is a single piece of knowledge about the game mechanics acquired through the successful completion of an interaction loop.

Until now, analytical tasks have been reserved for users and analysts, as only humans are involved in the analysis process as decision-makers [DS21]. We do not intend to challenge this, however, the role of guidance is to *support* analysis and, consequently, it takes part in the decision-making process. Thus, it is necessary to complement user's tasks models with guidance.

3. Model of Knowledge Generation in Guided VA

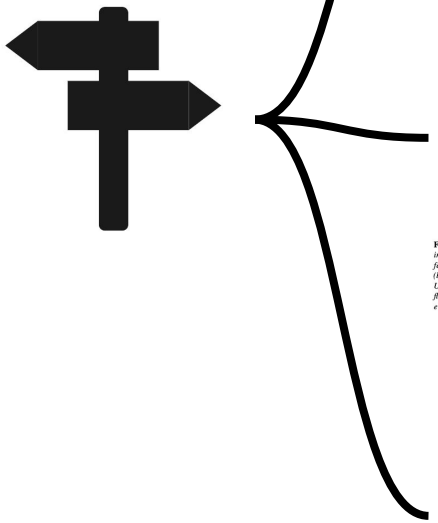
As we have seen, guidance and its role in the analysis are not typically considered when describing how knowledge is generated. Hence, in this section we provide an expanded version of the knowledge generation process, with the inclusion of guidance. We performed this expansion after analyzing existing guidance approaches [CGM19a]. We chose as a base for our discussion the Knowledge Generation Model described by Sacha et al. [SSS*14] because it provides a fine-grained view of the analysis process, matching well with the visualization tasks perspective, and for it being a fundamental inspiration for this work. The User Side is kept the same as in the original model (see top portion of Fig. 1). Our expansion considers the addition of a "Guide Side" (bottom portion of Fig. 1), opposed to the User Side, which interacts with the Computer

Guidance Degrees

Directing guidance

A ranked set of options for the user to choose from

Partially constraints user action



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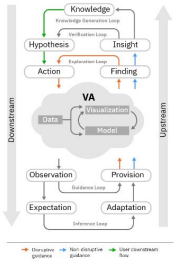


Figure 1: *The Model of Knowledge Generation in Guided VA showing how guidance contributes to the progress of the analysis. The different arrows model the interactions between User (top) and Guide (bottom). Downstream (User-to-Guide) and Upstream (Guide-to-User) arrows signal the two directions in which information can flow. The model is an expansion of the well-known Knowledge Generation Model. [SSS*14].*

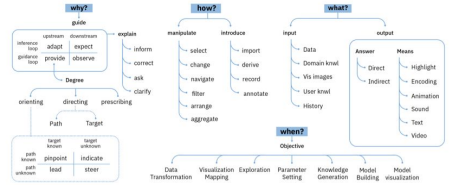


Figure 3: *Typology of system guidance tasks. It spans the three dimensions of the multi-level visualization task typology [BM13] plus a new dimension that captures the analytical objective of an analysis phase (*when?*). It allows describing: system task intent (*why?*) by different detail levels (aim, first- and second-order degree), also with an accompanying explanation task (*explain*); the suggestion method (*how?*) in terms of data manipulations and means of communication; and the information inputs and type of output relative to the targeted user task (*what?*).*

8. Conclusion

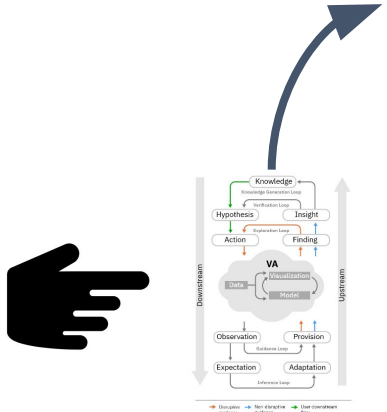
We have presented a typology of system guidance tasks that enables a joint analysis of user and guidance task interdependence, illustrating it with different examples. We have also shown the effects of guidance over user tasks and vice versa, deriving finer-grained guidance degrees in the process. This is supported with a model of guidance within the VA knowledge generation process. Our typology appears to serve well the purpose of describing, abstracting, and generalizing VA systems with mixed-initiative approaches, providing succinct representations that we hope will enrich the incursion into guidance design and improve the communication of results, stimulating the production of guidelines that, with time and testing, may expand design considerations in VA.

Guidance Degrees

Prescribing guidance

Mandatory actions or step-by-step instructions that can be automatically enacted on acceptance

User action is constrained to either accepting or declining



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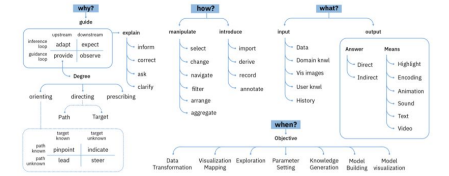

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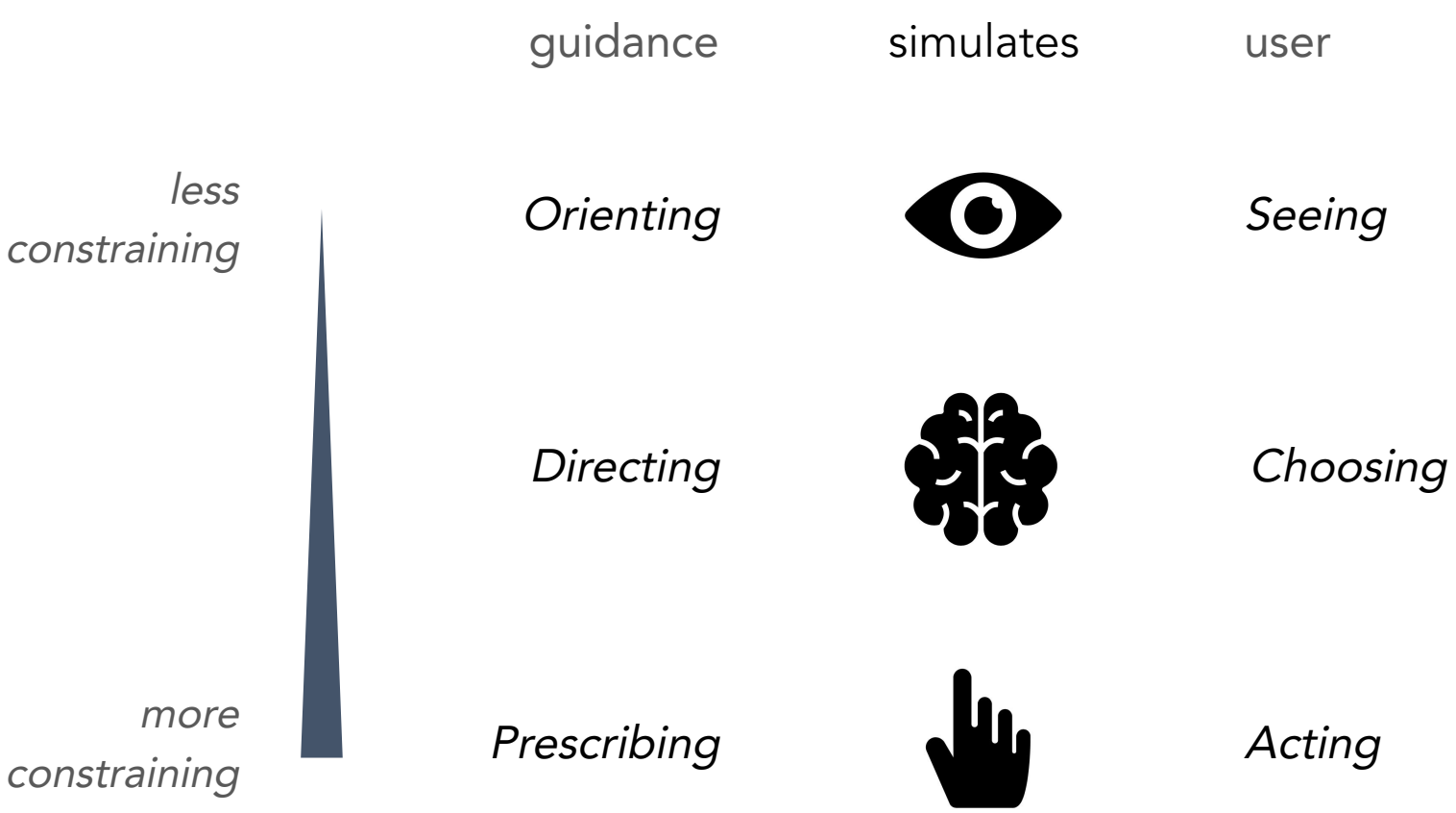
Guidance Degrees



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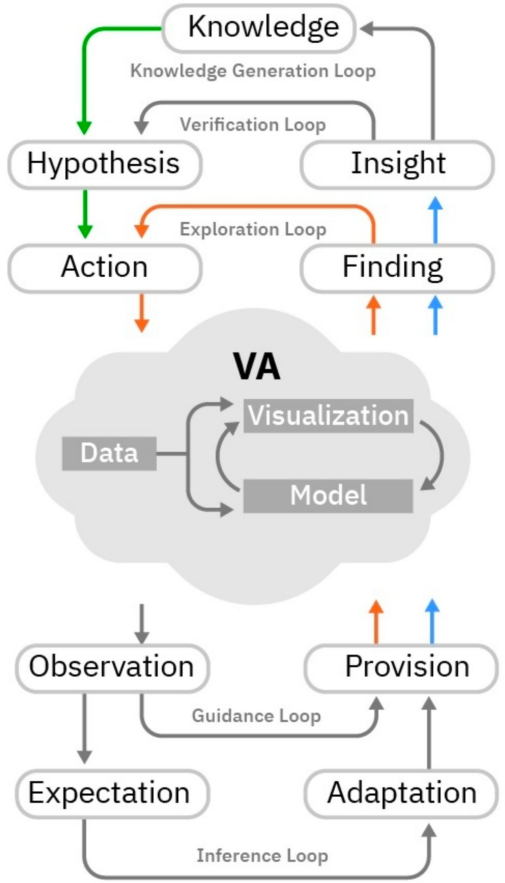
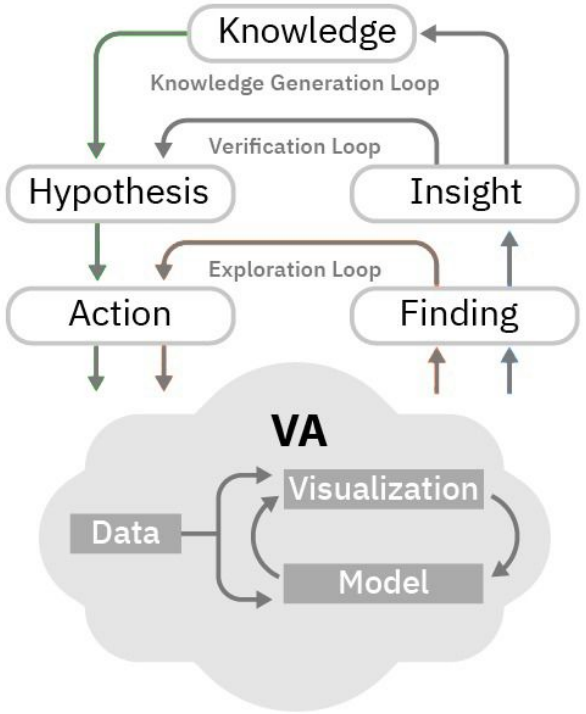


Model of Knowledge Generation in Guided VA

Knowledge Generation Model



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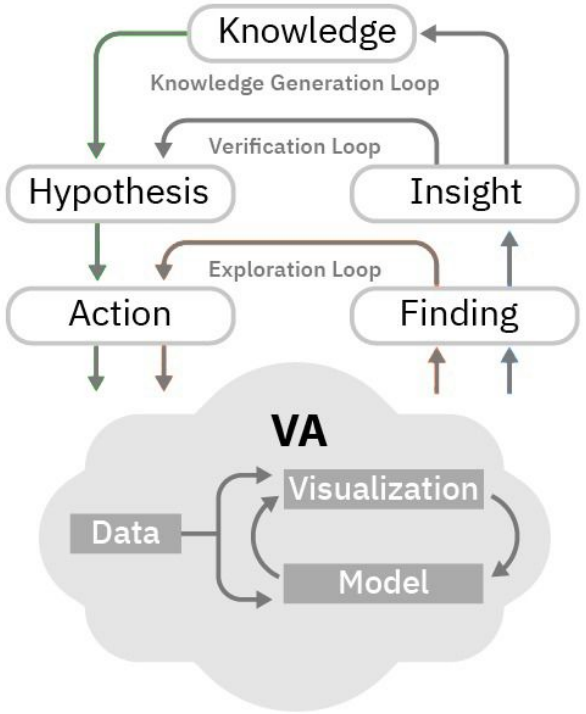
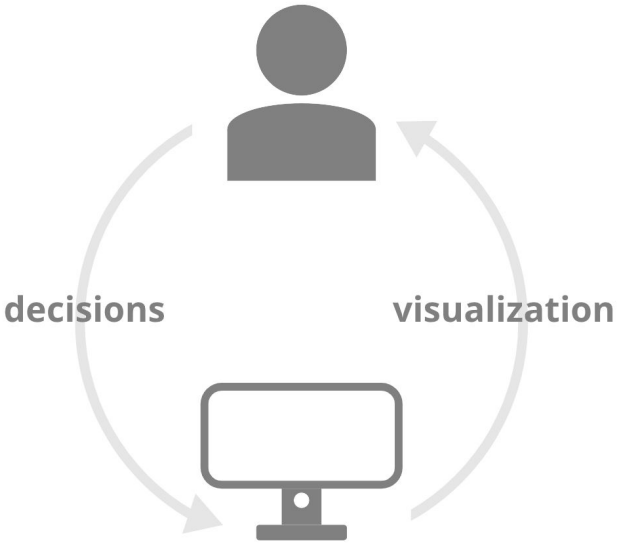
Model of Knowledge Generation in Guided VA

Knowledge Generation Model





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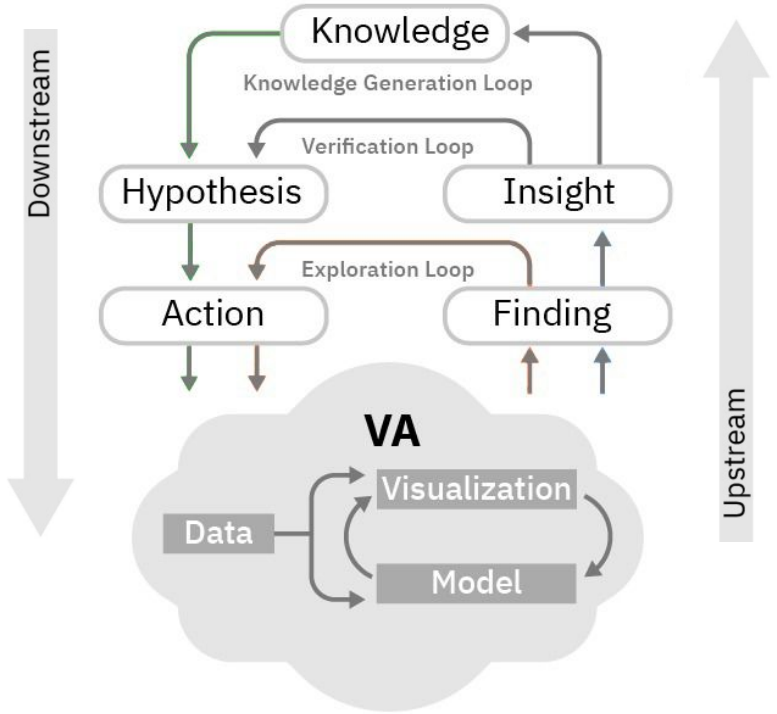
Model of Knowledge Generation in Guided VA

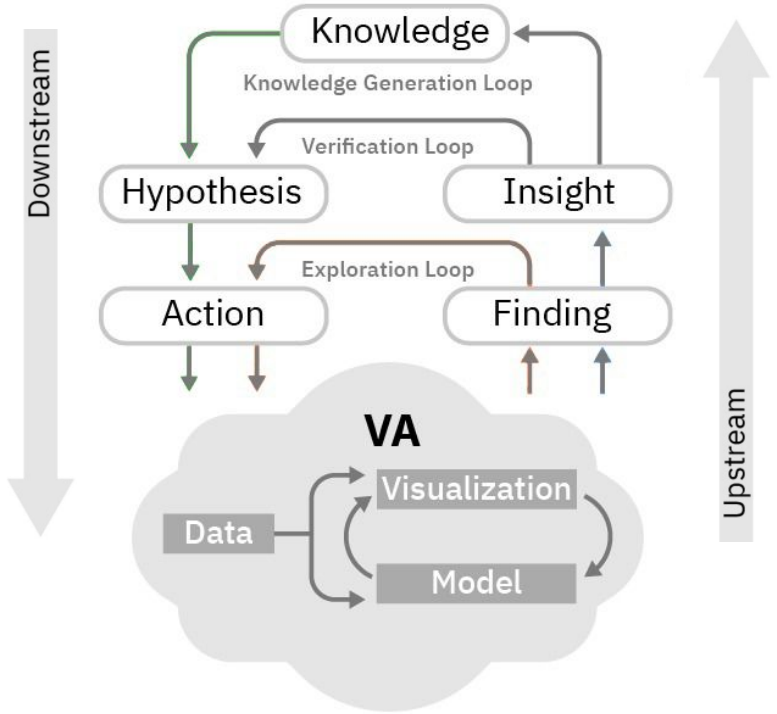
Information flow directions

- Upstream (to the user)
- Downstream (to the system)



Model of Knowledge Generation in Guided VA

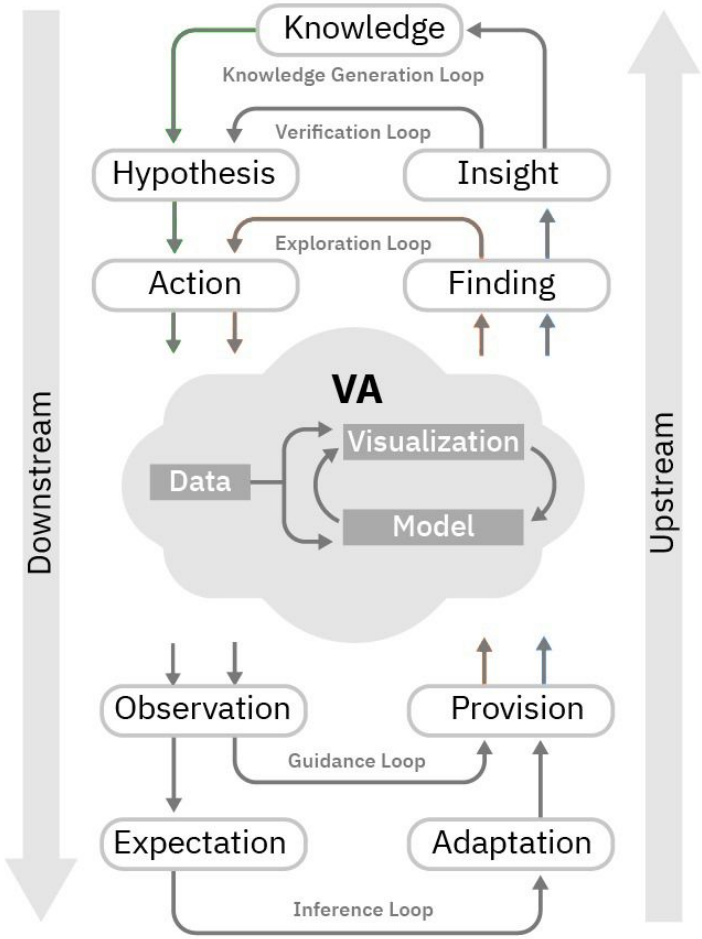
The Exploration Loop is the basic interaction loop



Model of Knowledge Generation in Guided VA

Guidance side

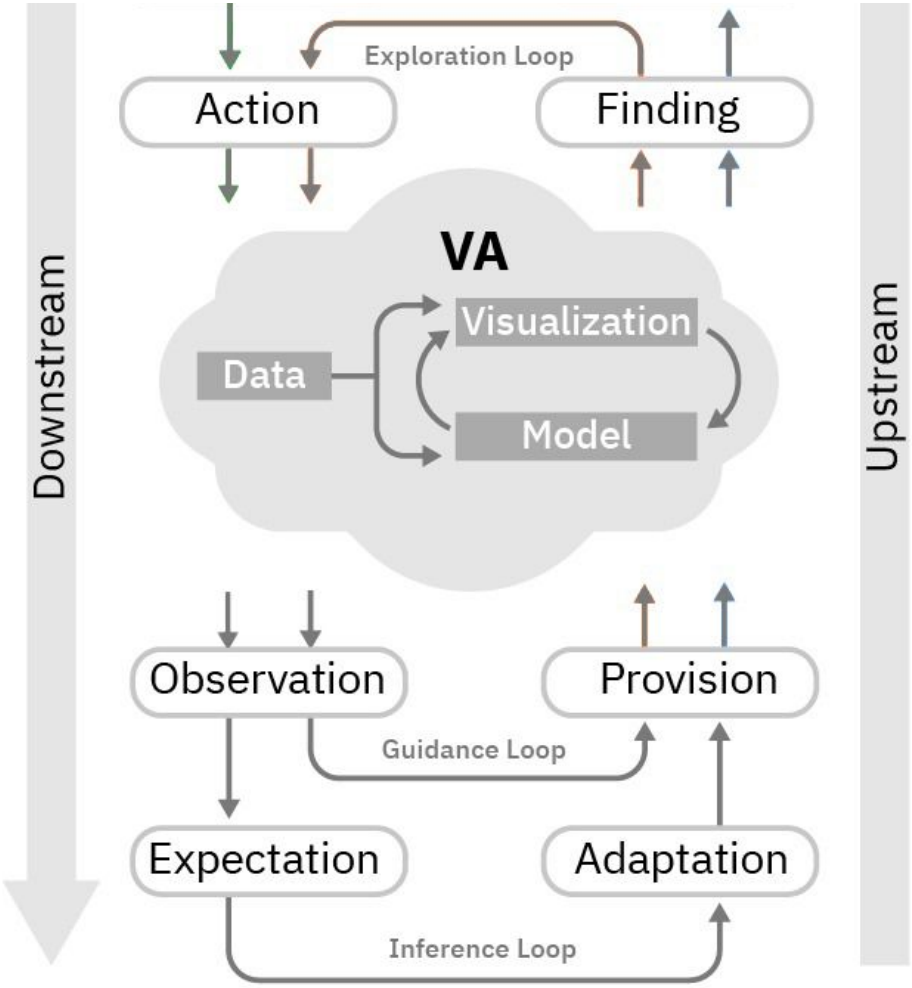
It interacts with the user through the VA system



Model of Knowledge Generation in Guided VA

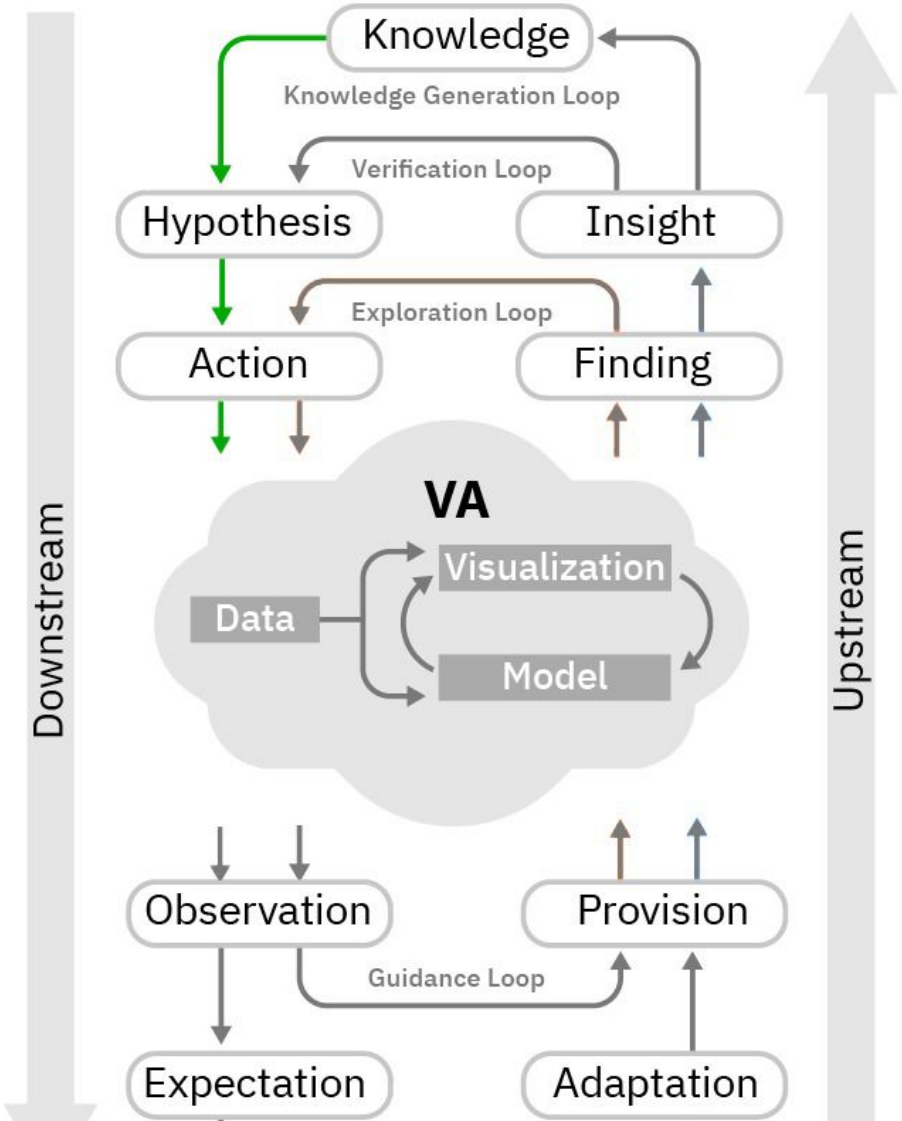
Guidance Loop
First-order loop of interaction with the user

Inference Loop
Second-order loop of self-interaction



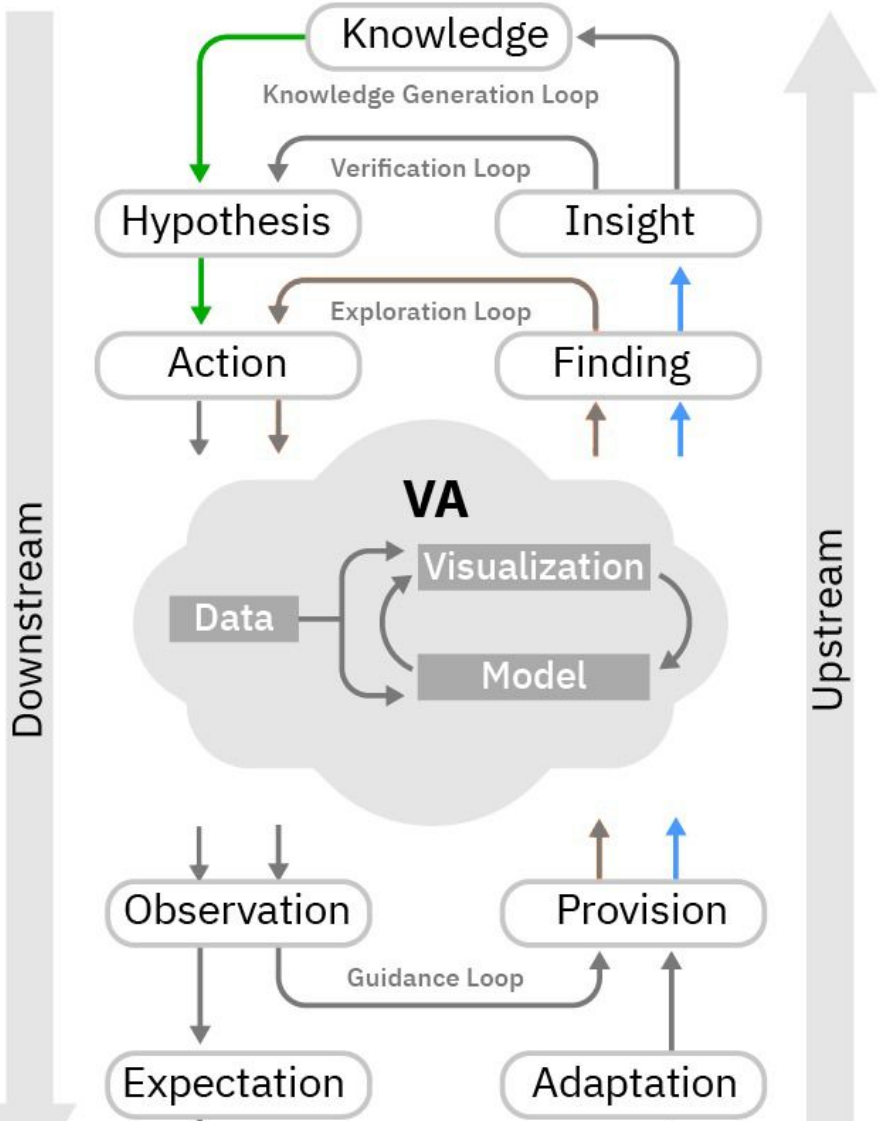
Model of Knowledge Generation in Guided VA

Information from the users' analysis process flows downstream and is observed by the guidance system



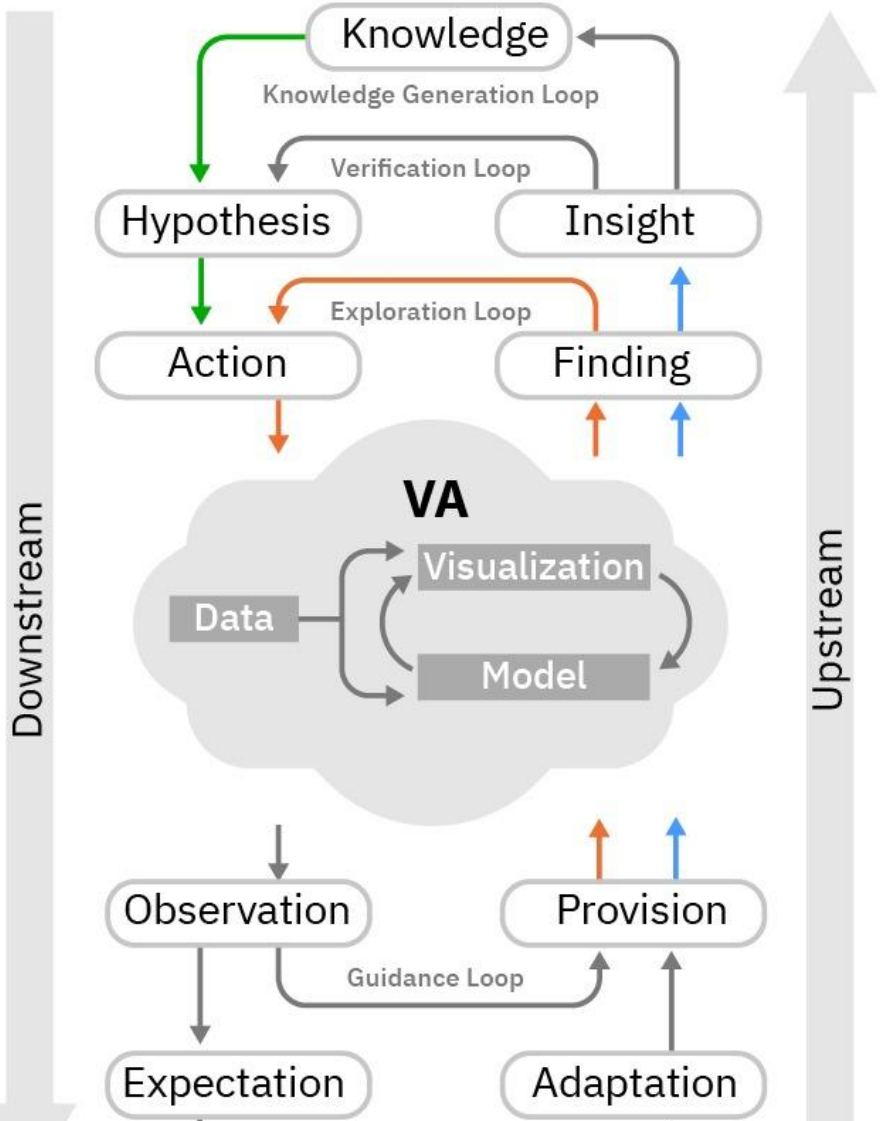
Model of Knowledge Generation in Guided VA

Guidance (non-disruptive) is provided upstream



Model of Knowledge Generation in Guided VA

Disruptive guidance is provided and fed back into the system, short-circuiting the exploration loop



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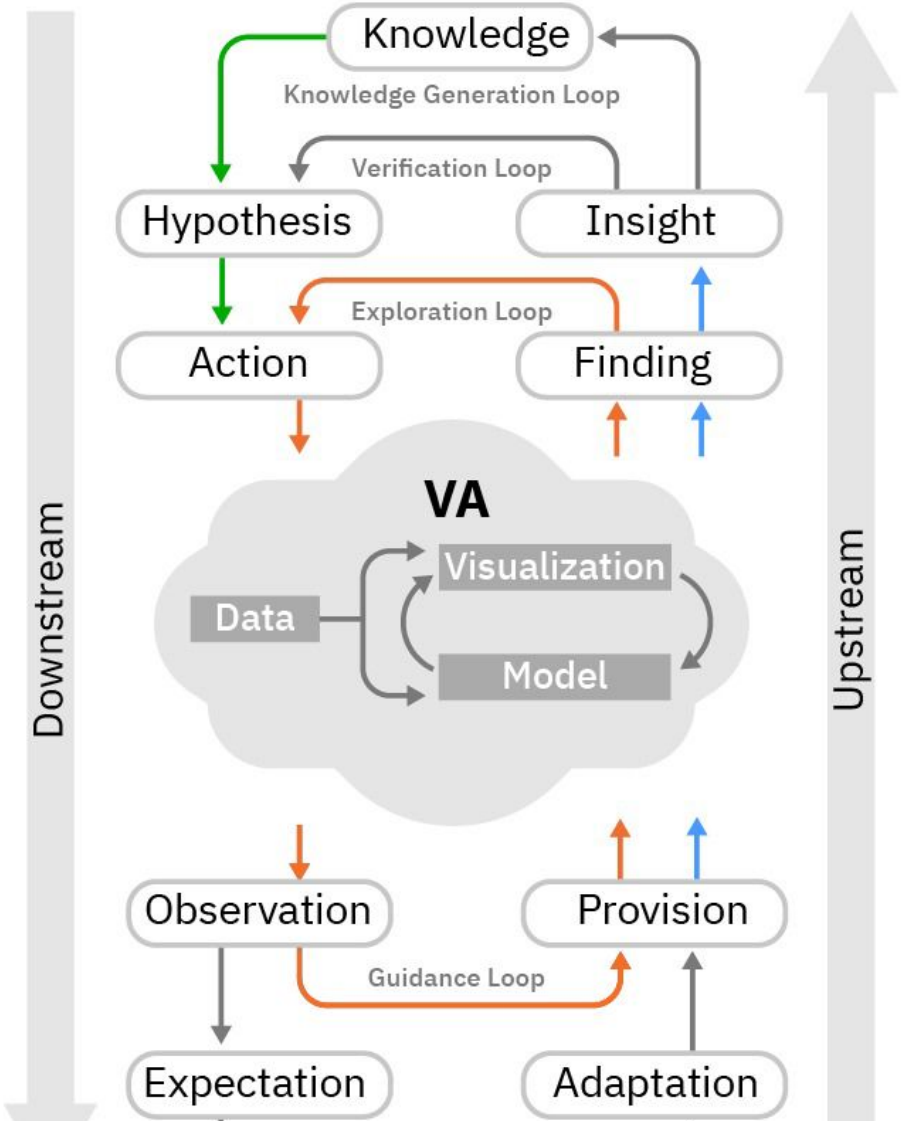
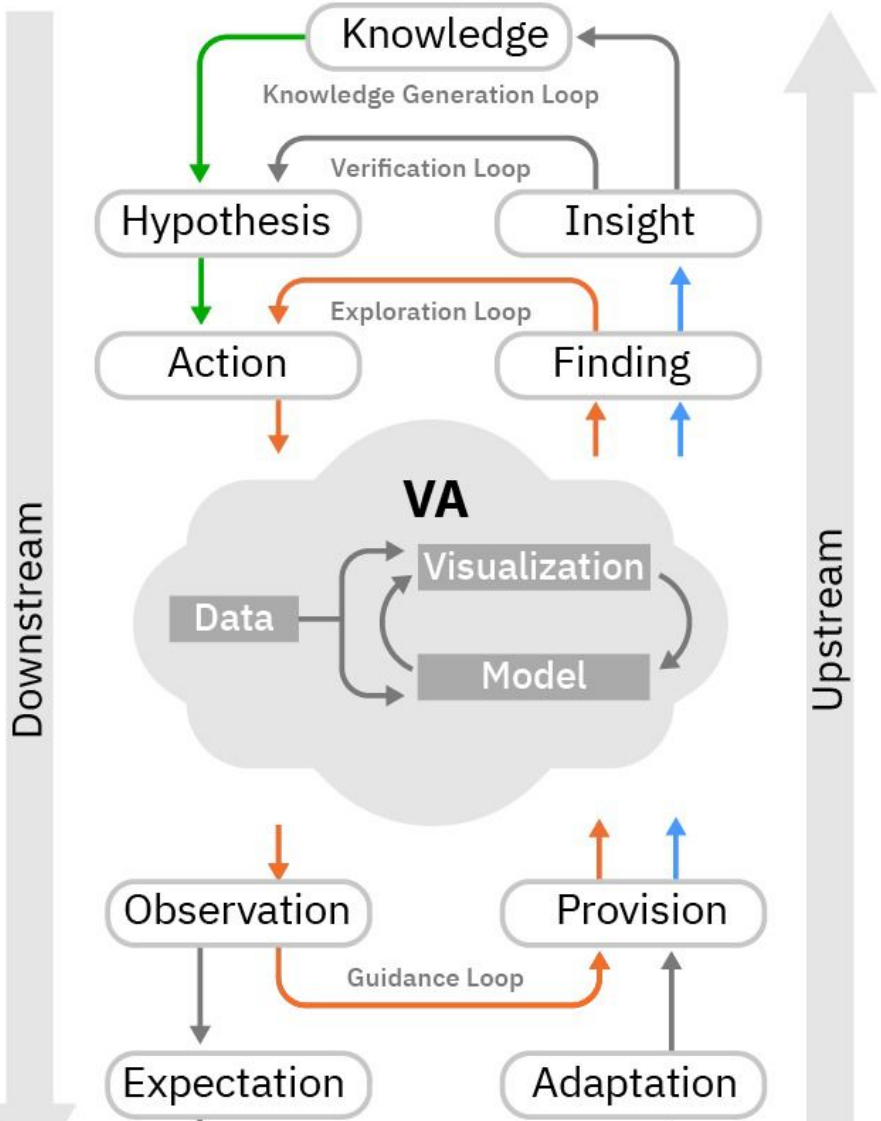


Model of Knowledge Generation in Guided VA

Where does the difference between disruptive and non-disruptive guidance stem from?



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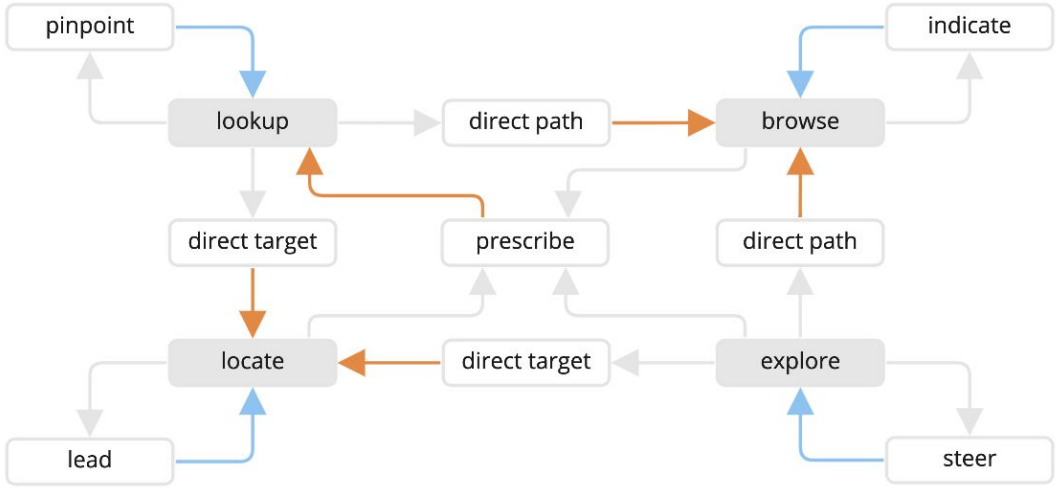
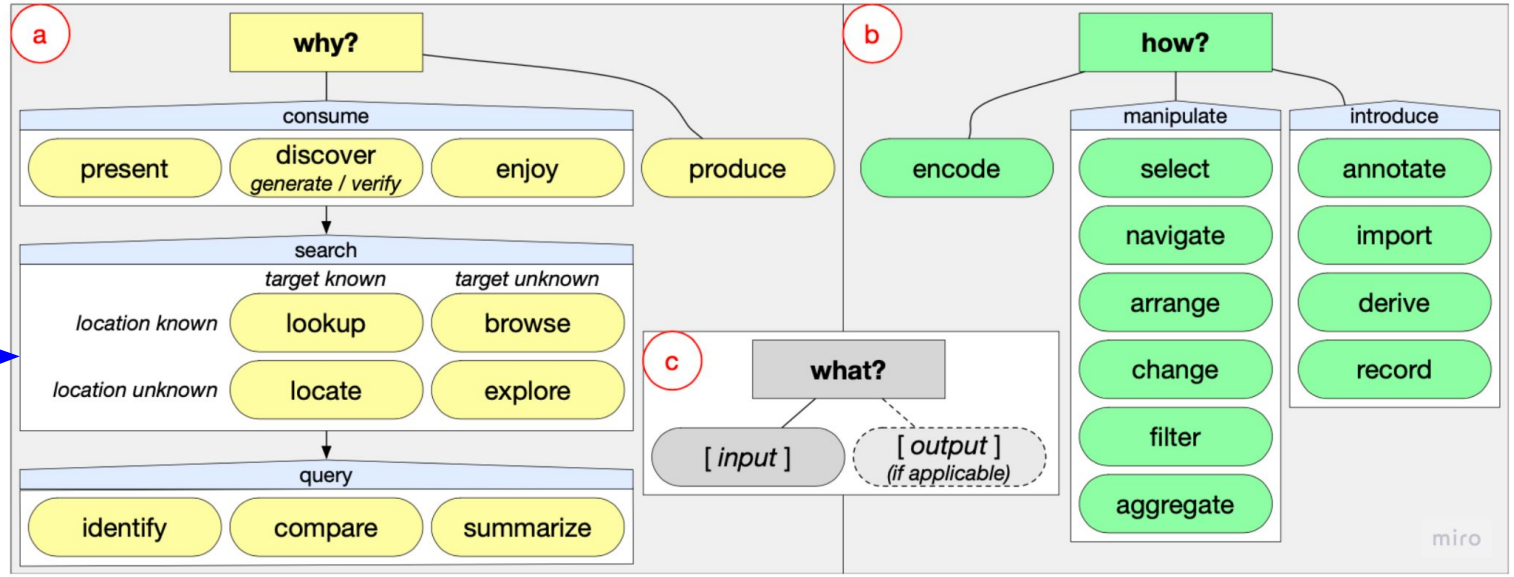


User Tasks

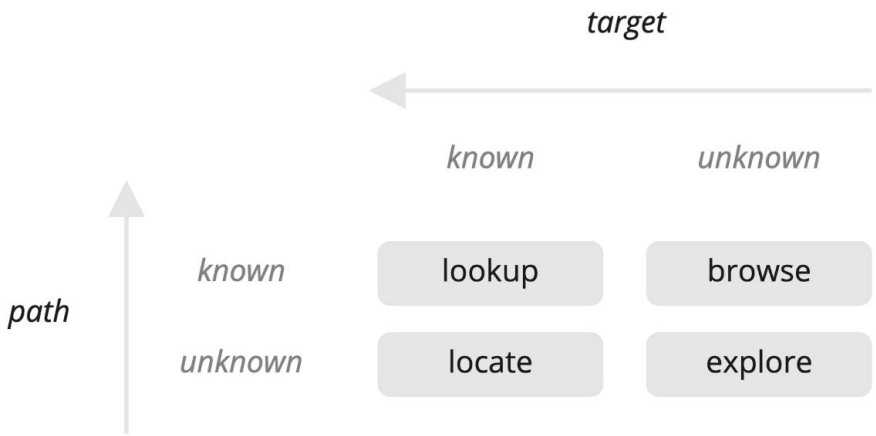
Multi-level Typology of Abstract Visualization Tasks

Search types define the complexity of the task



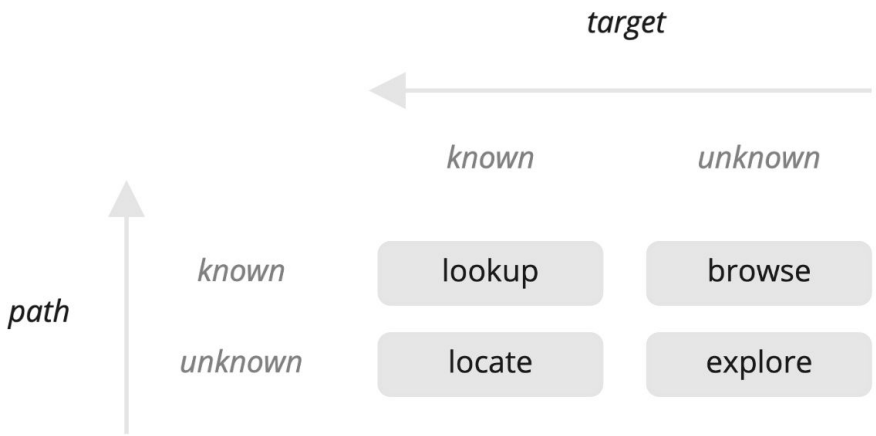
Search Types

Search types define the space where the target and path of analysis are either known or unknown to the user



Perspective change

The movement from one search task to another during analysis



Perspective change

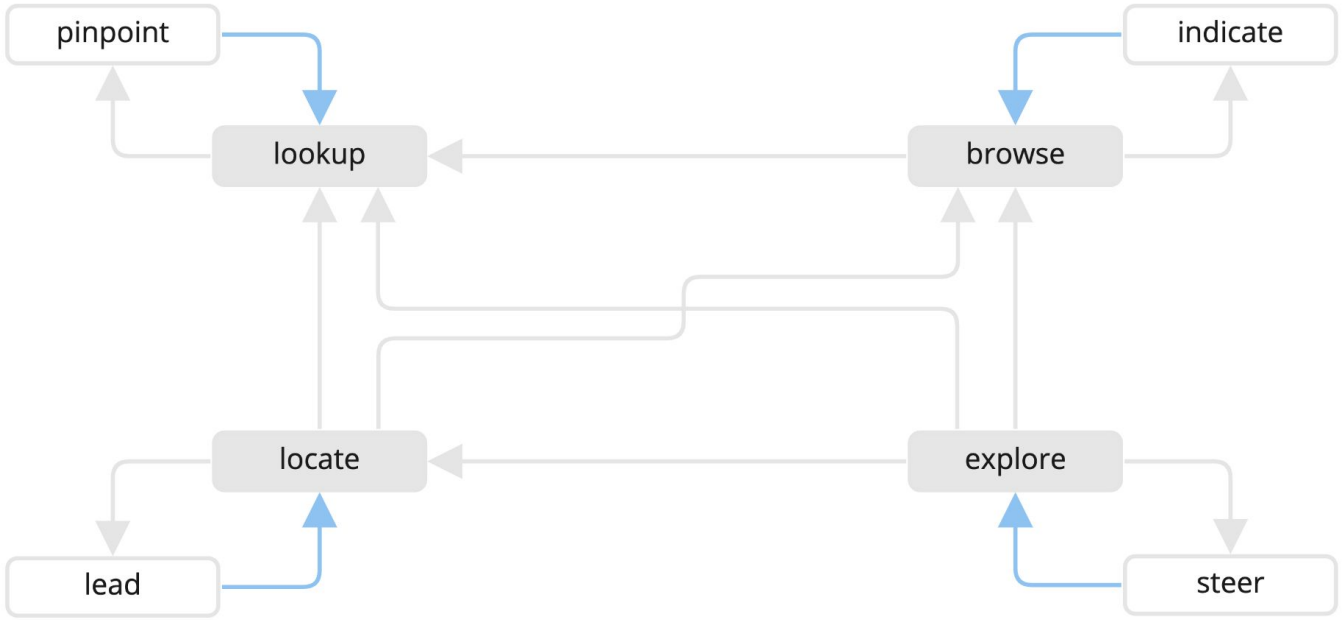
Arrows point in the direction of decreasing complexity

Perspective change

Orienting
Lowest degree of guidance

Does not constrain action

A second-order degree is defined for each user task being targeted

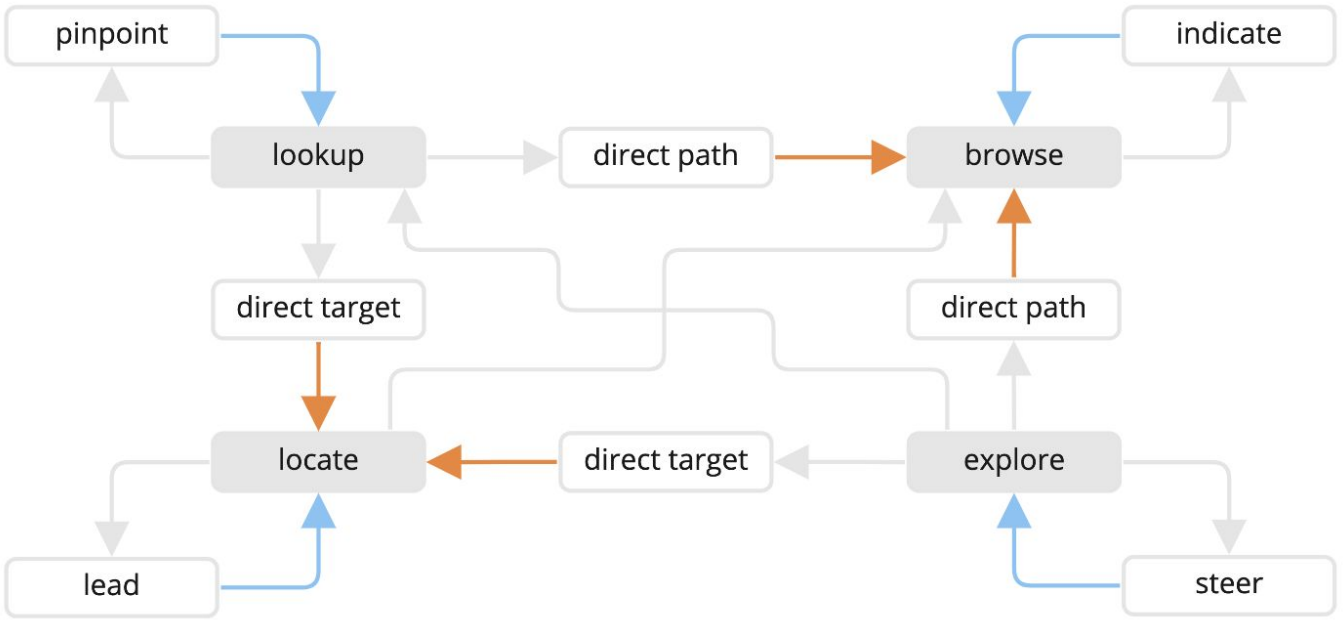


Perspective change

Directing
The middle degree of guidance

Leads to *browse* and *locate tasks*

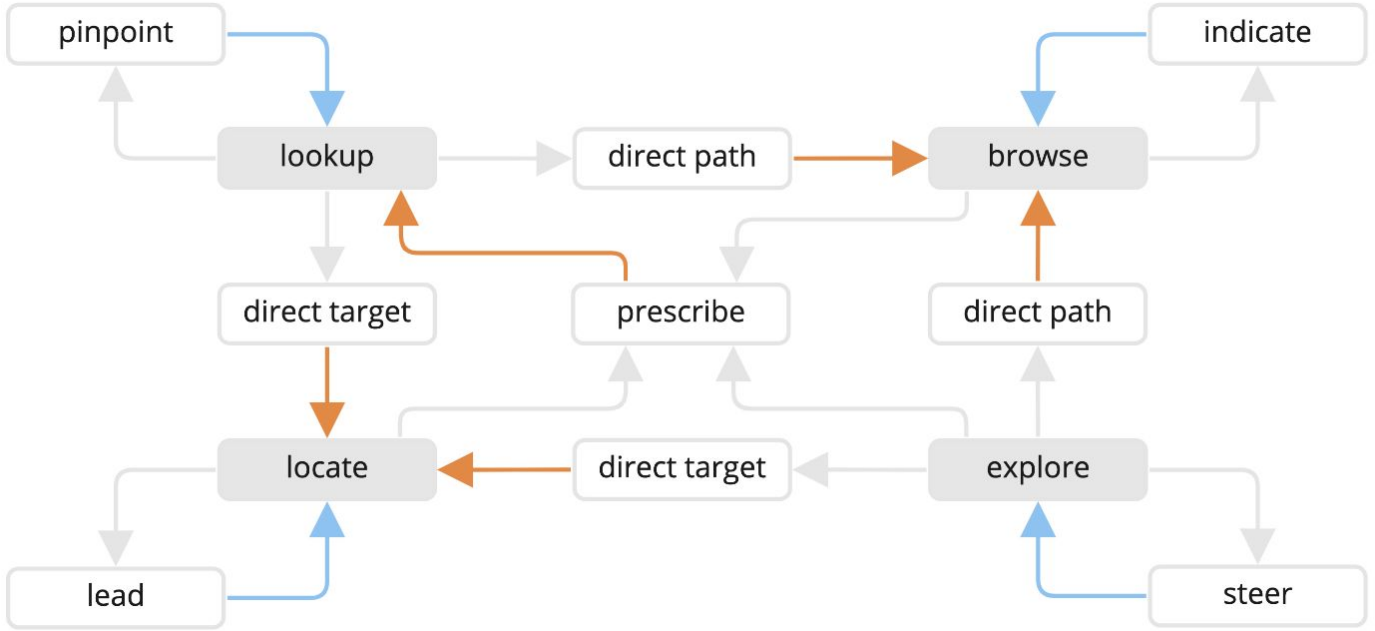
Two second-order degrees depending on the axis it moves the task: *path* and *target*



Perspective change

Prescribing
The highest degree of guidance

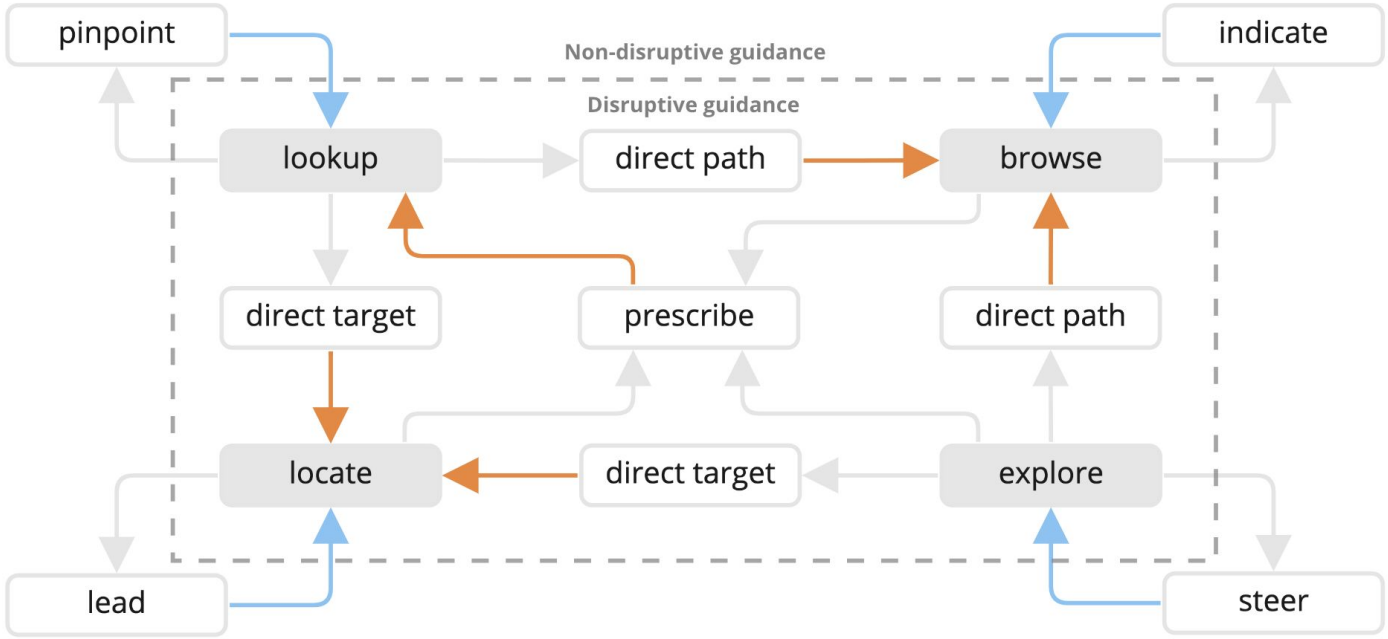
By constraining all user action
drives any task to a *lookup*



Perspective change

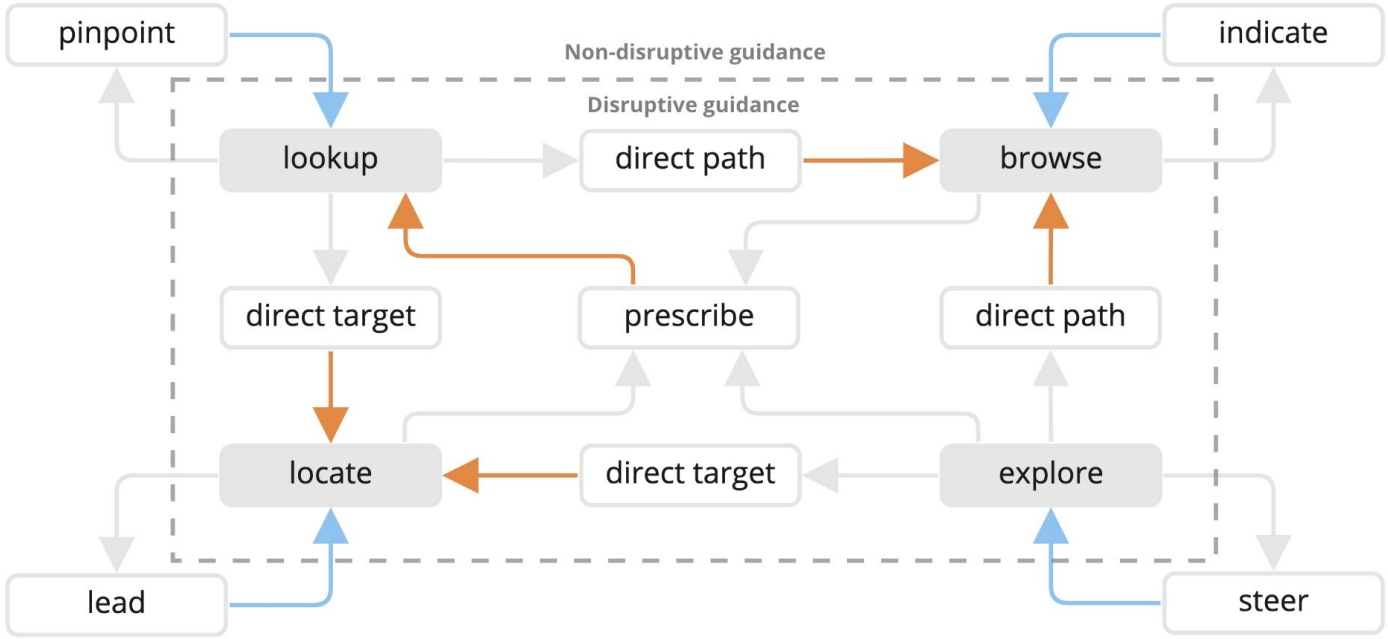
Non-disruptive guidance correspond to guidance tasks that do not change the user task

Disruptive guidance corresponds to guidance tasks that induce perspective change on the user



Perspective change

If a user tasks is defined by a kind of search, a guidance task is defined by its intended effect over this search.



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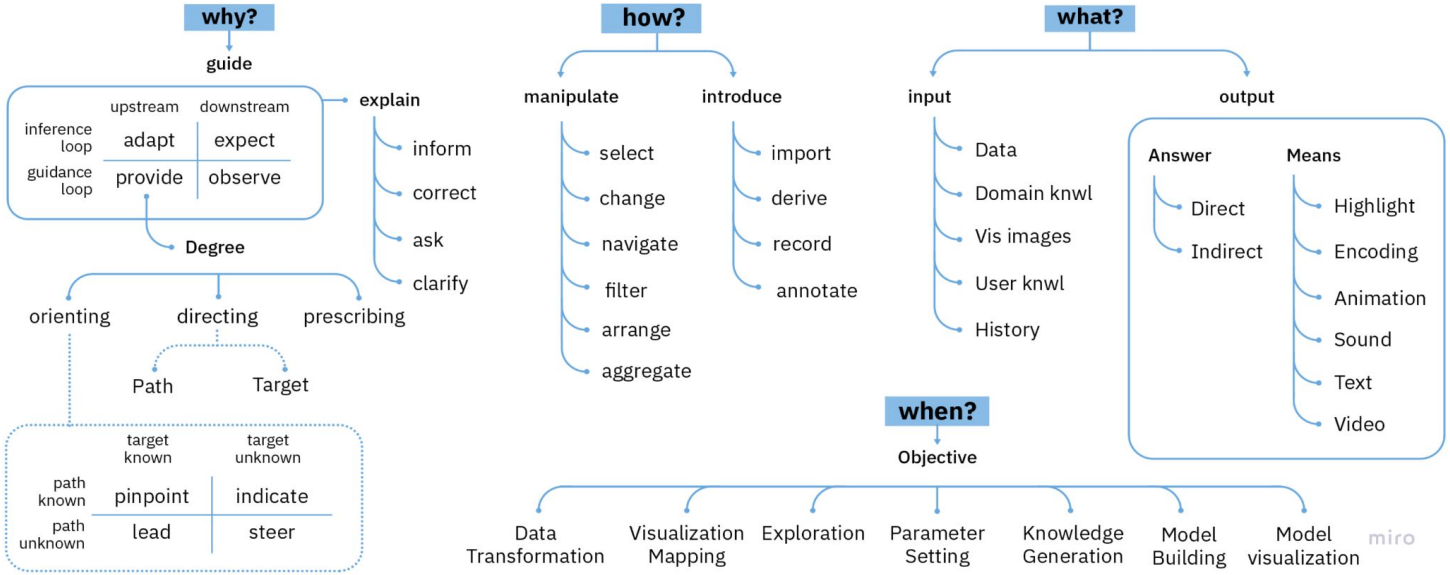
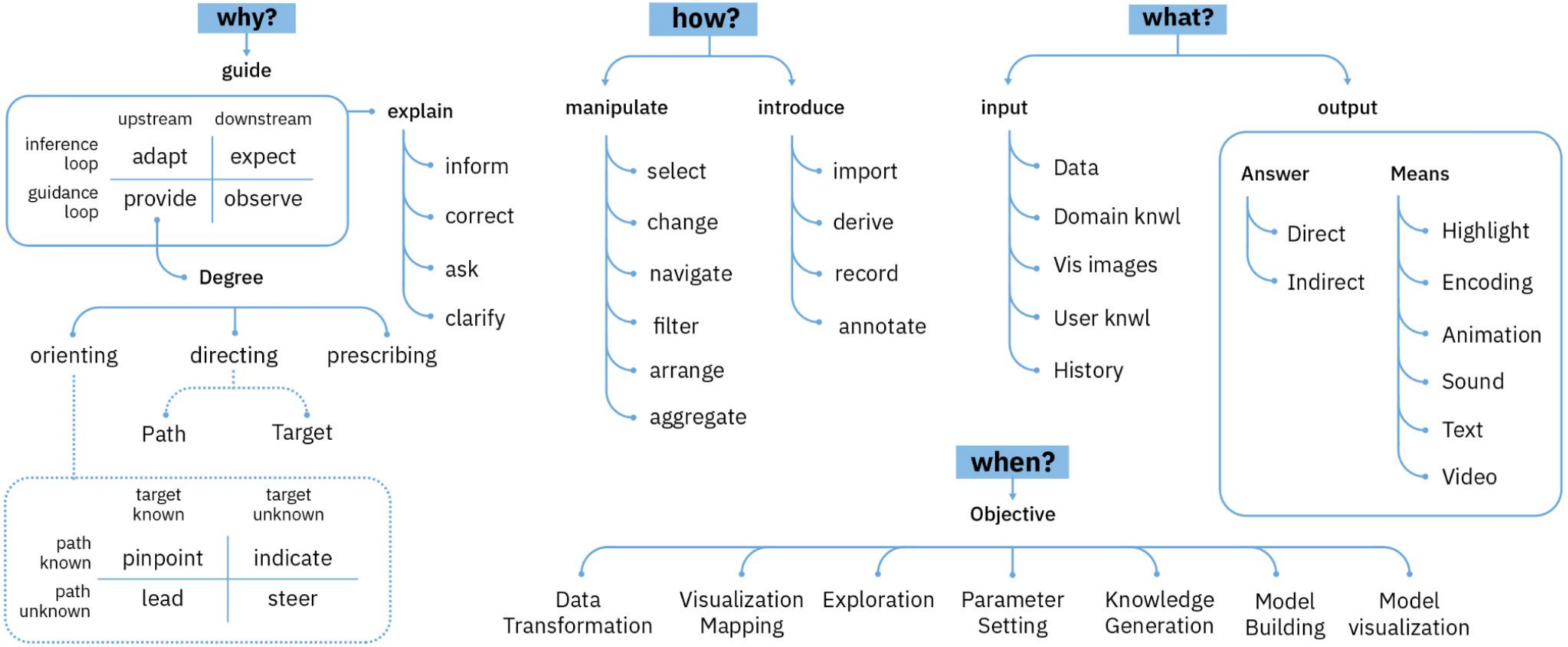
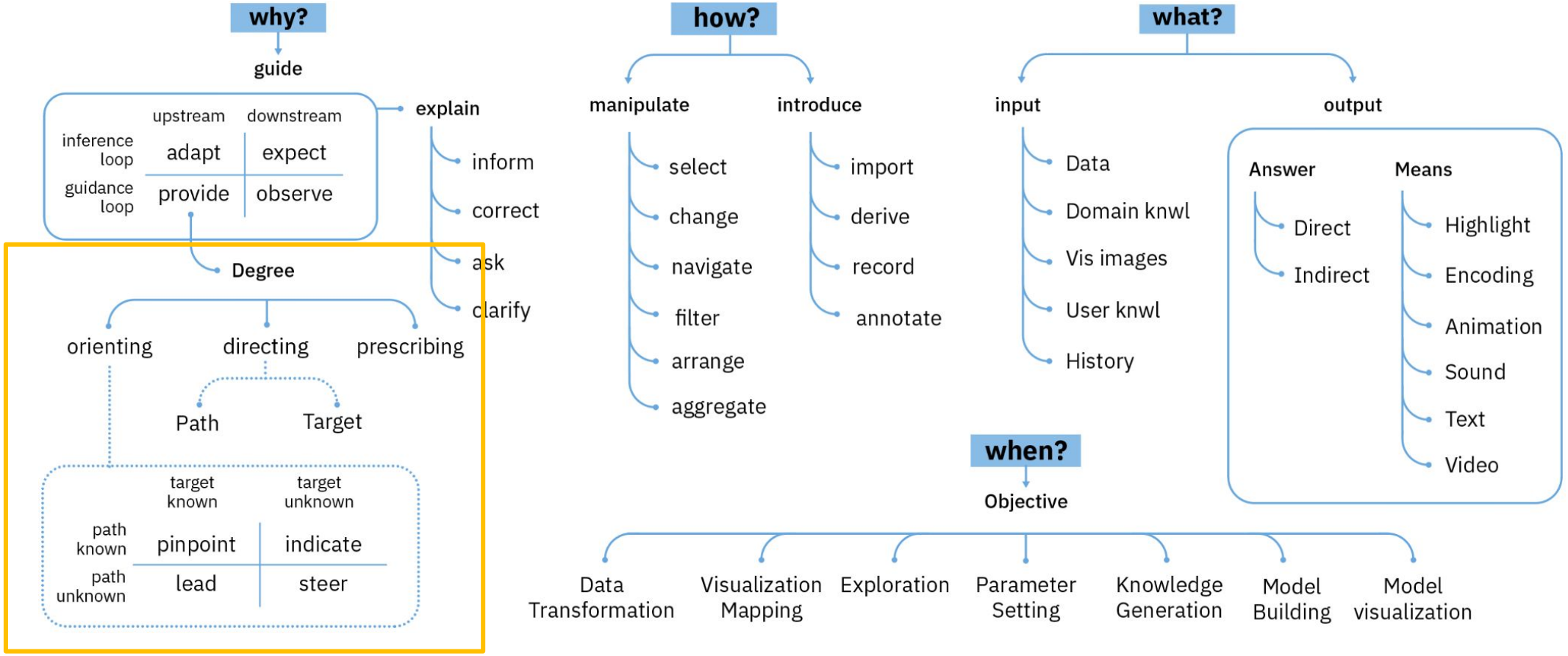


A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

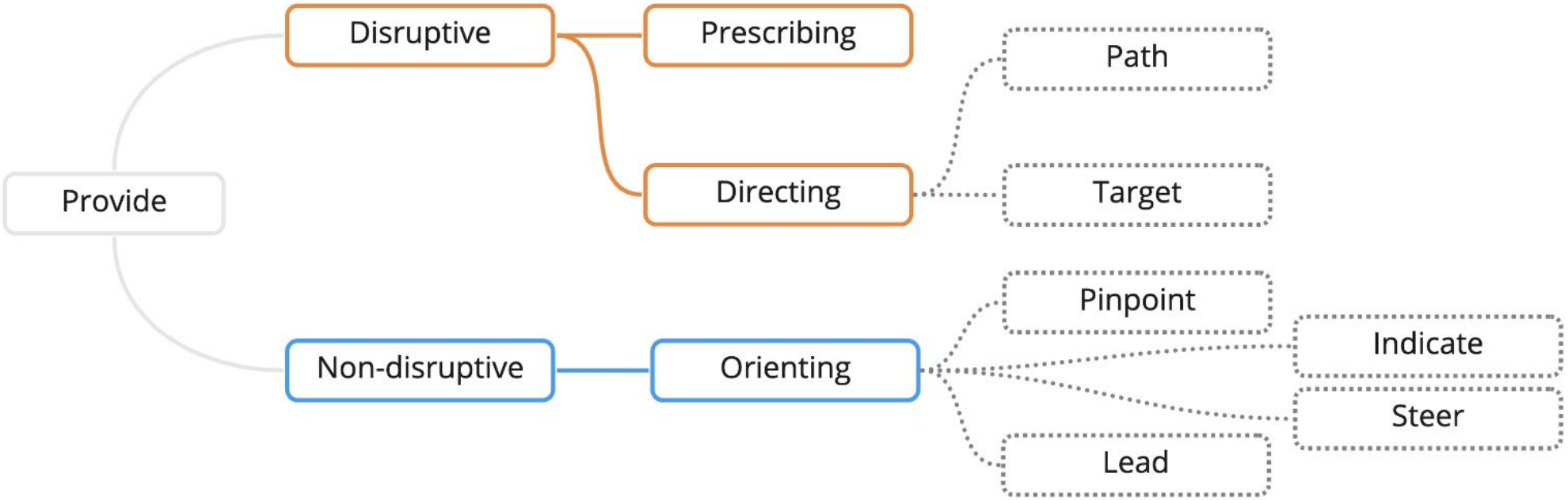


3+1 Dimensions

A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments



Semantic Zoom on guidance provision



Using the typology

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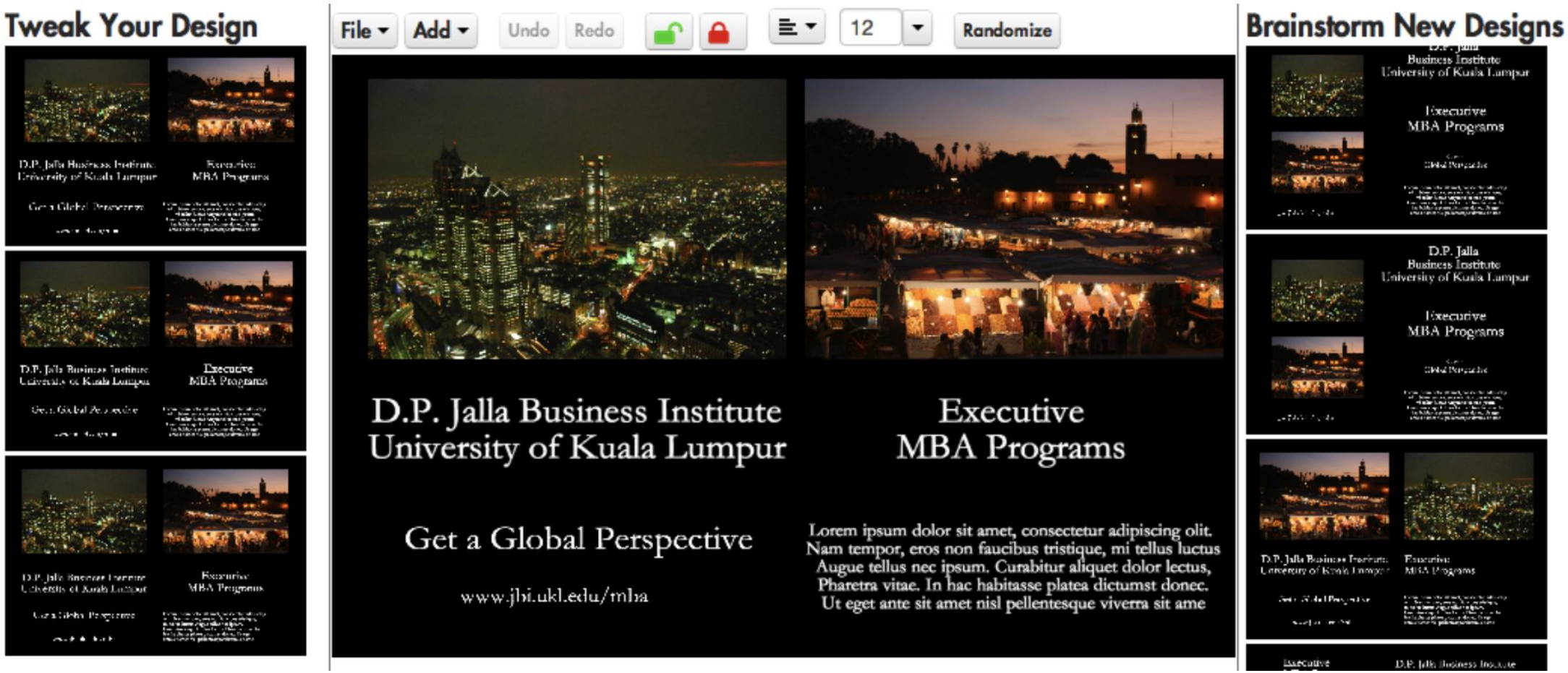
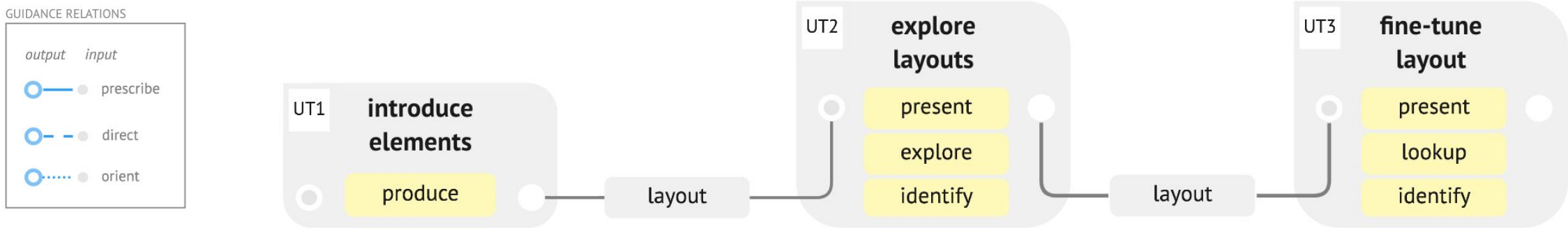
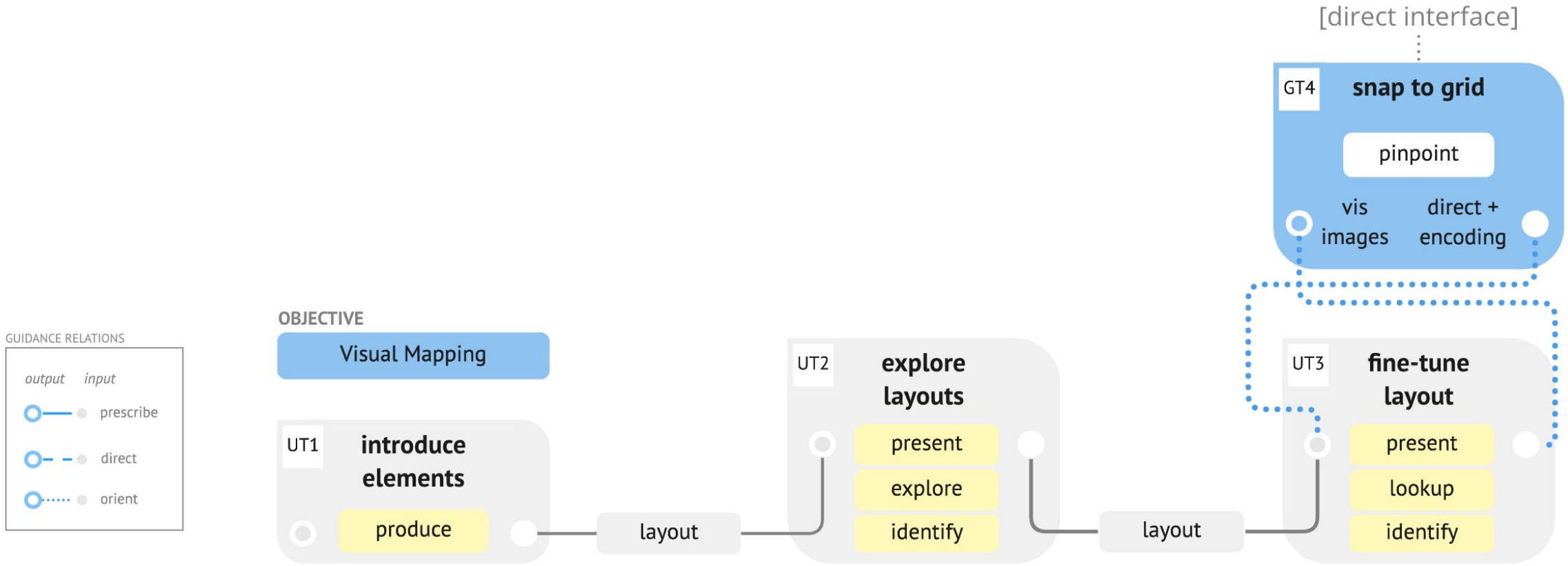


O'Donovan, P., Agarwala, A., & Hertzmann, A. (2015, April). Designscape: Design with interactive layout suggestions. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems* (pp. 1221-1224).

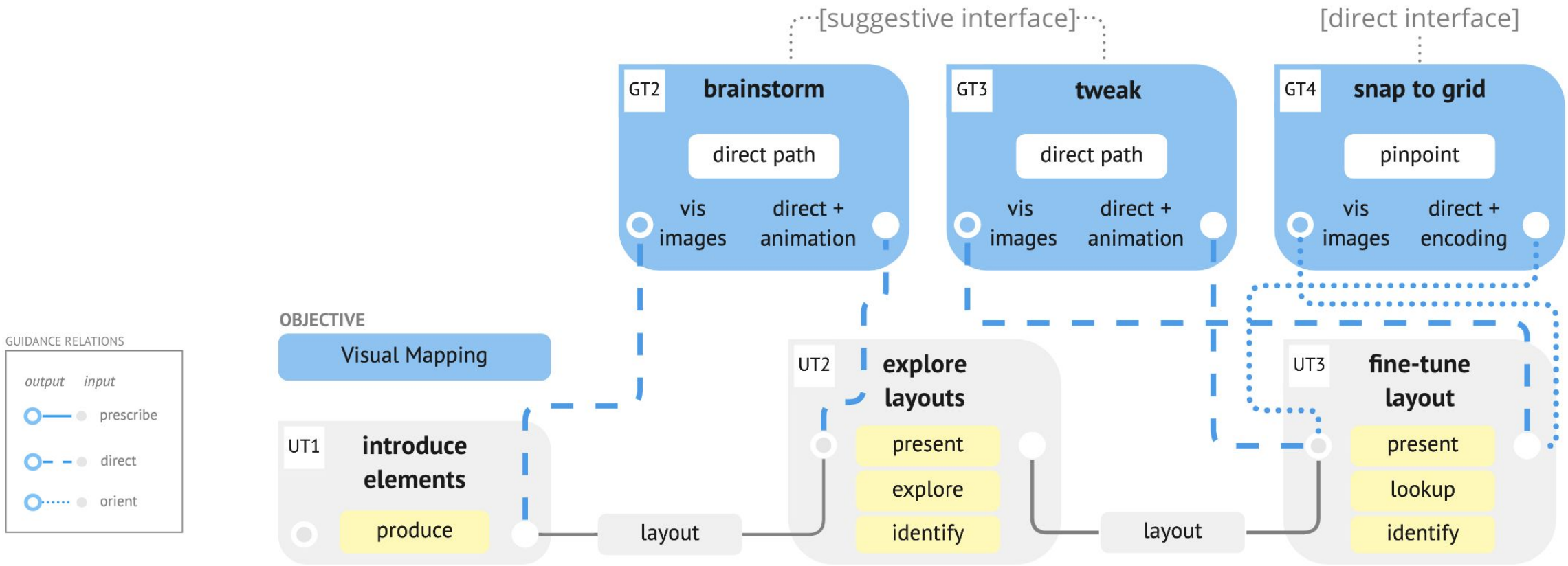
Case studies
DesignScape



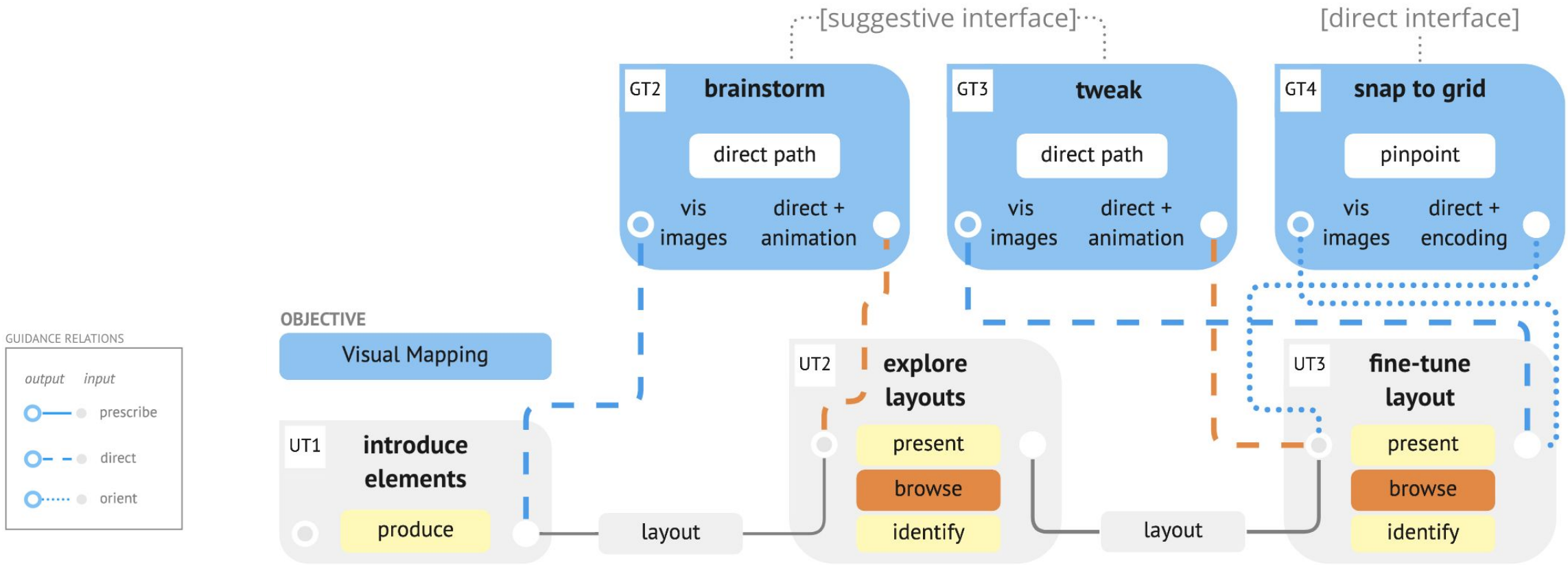
Case studies
DesignScape



Case studies
DesignScape



Case studies
DesignScape



Case studies
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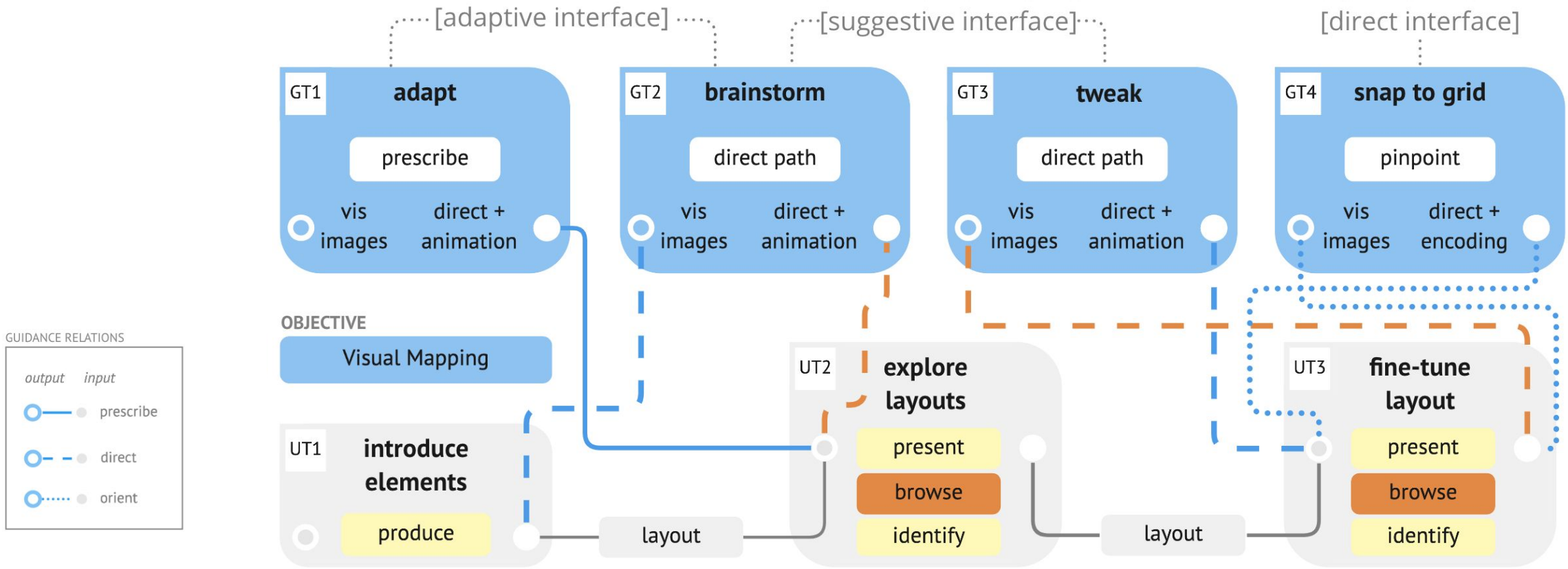
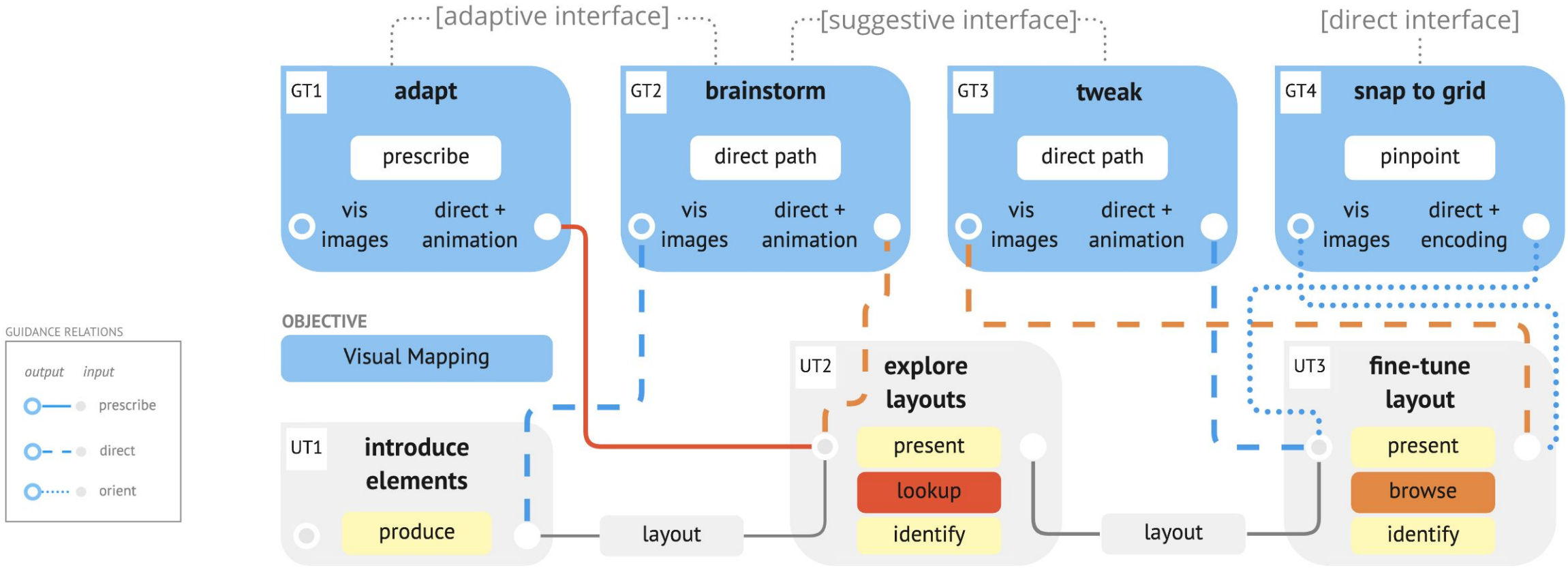
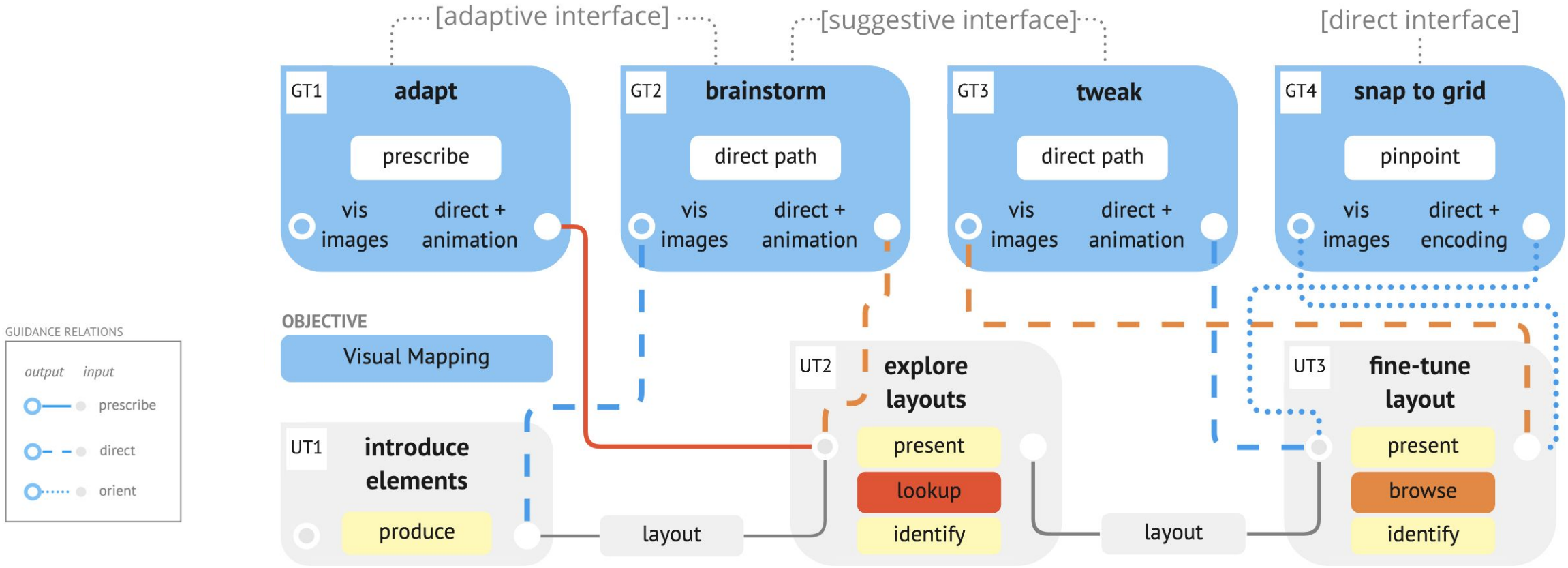


Case studies
DesignScape

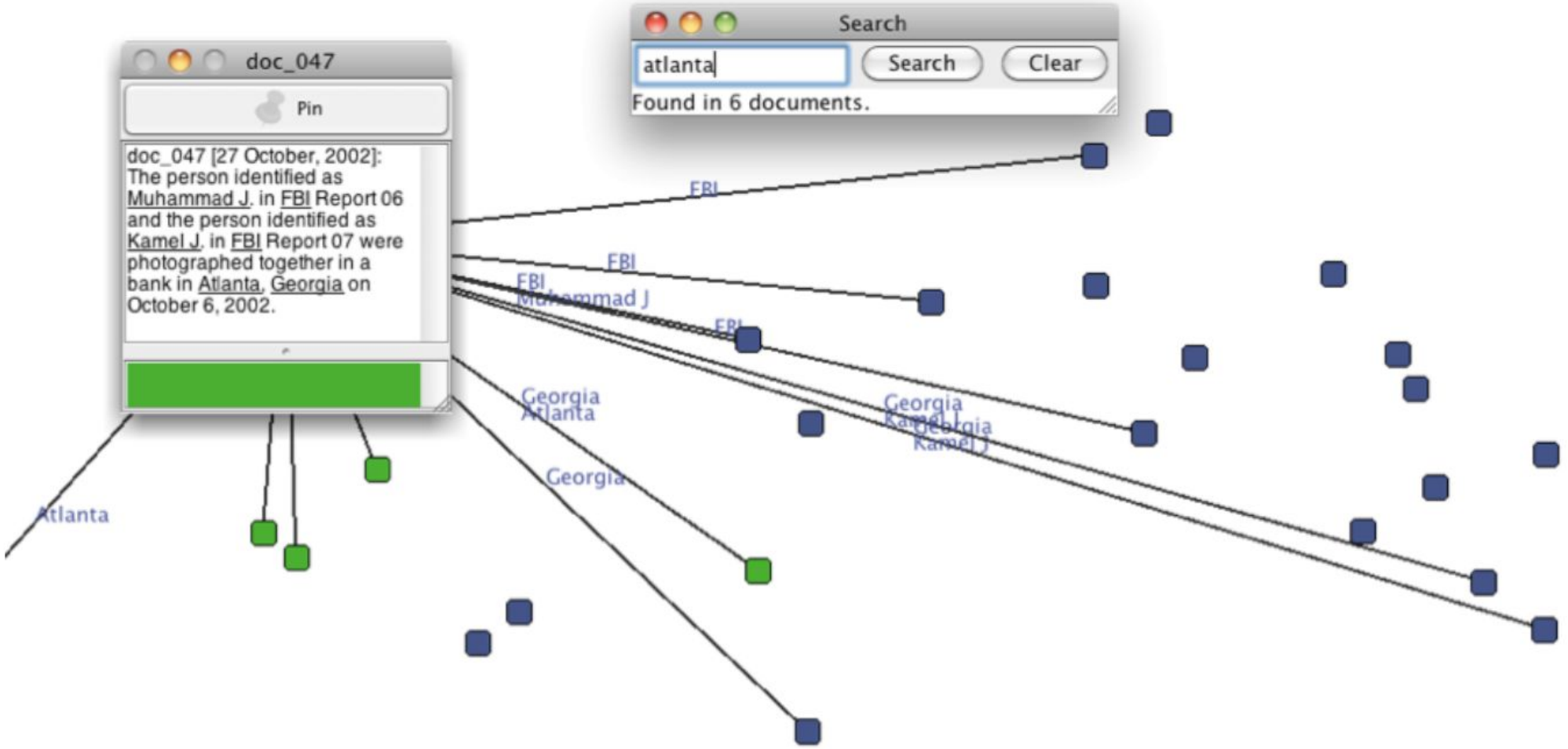


Case studies
DesignScape



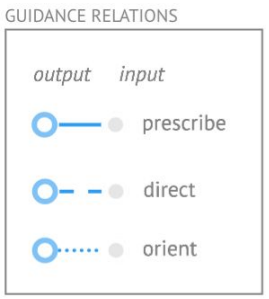
Users felt frustrated by the lack of agency in solutions they found nonetheless good (using the adaptive interface).

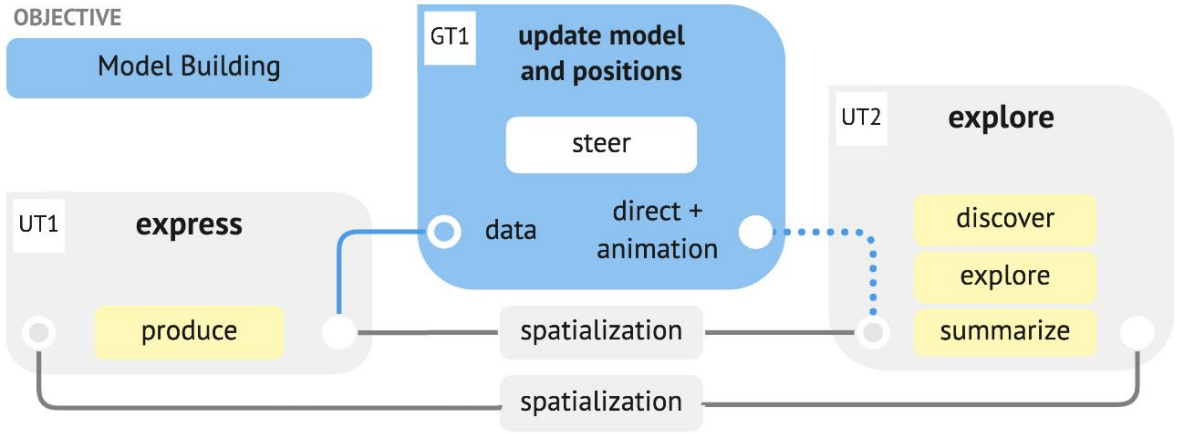
Case studies
ForceSPIRE

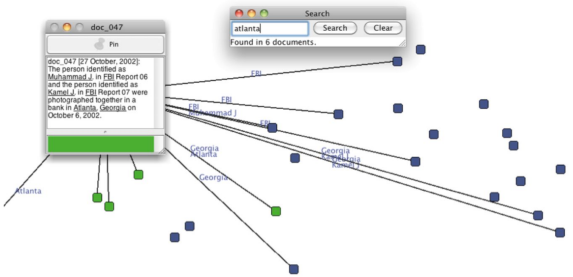


Endert, A., Fiaux, P., & North, C. (2012, May). Semantic interaction for visual text analytics. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 473-482).

Case studies
ForceSPIRE







Case studies
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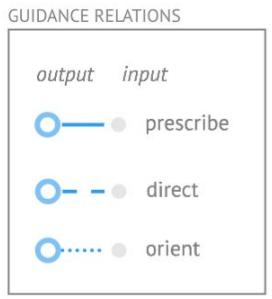
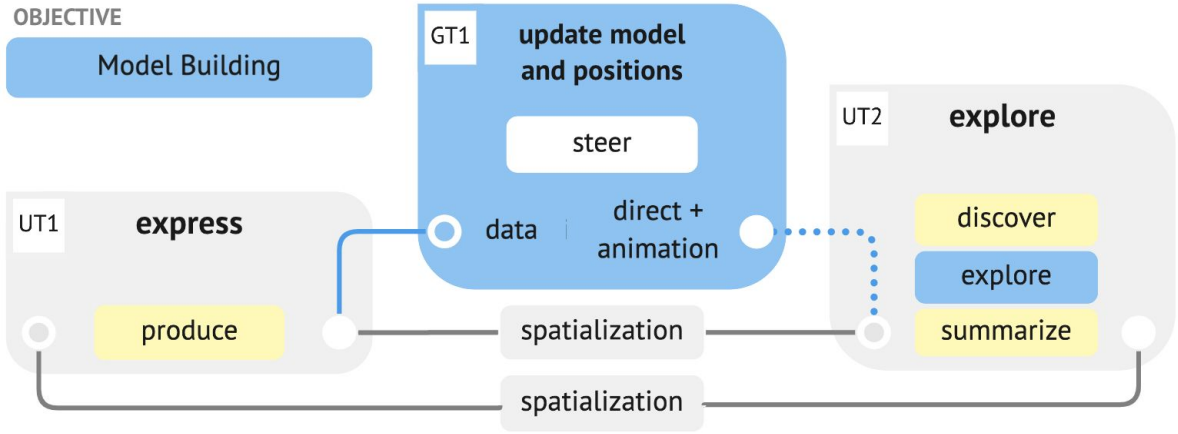
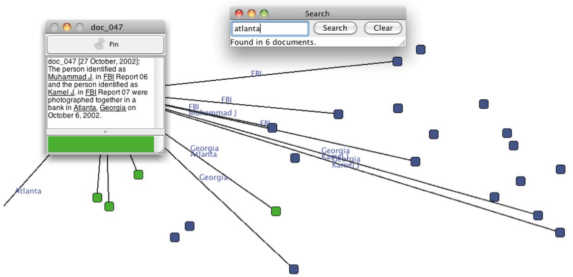
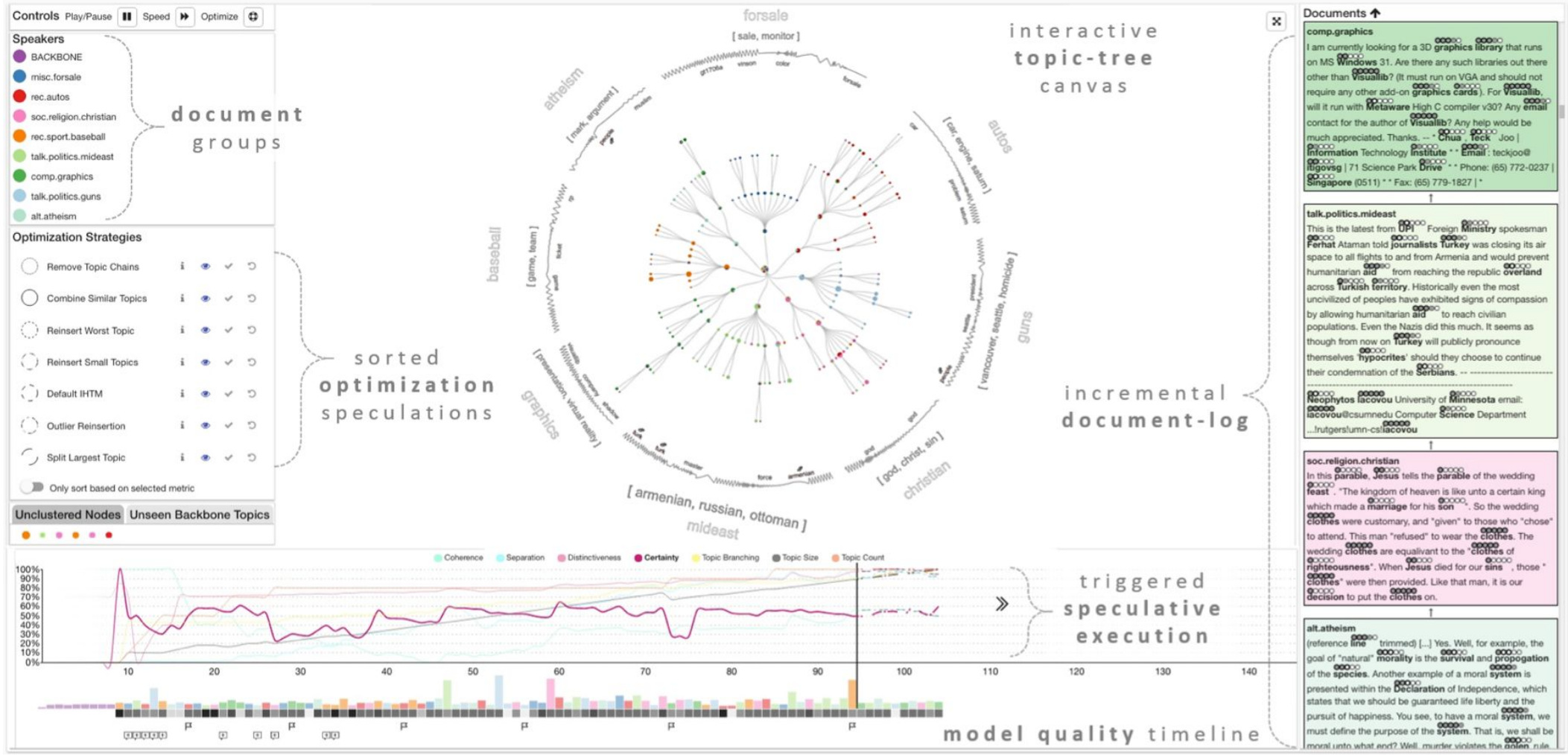






"[Users] treated their investigation not as *steering* a model, but rather synthesizing information"

Case studies
Topic-Tree



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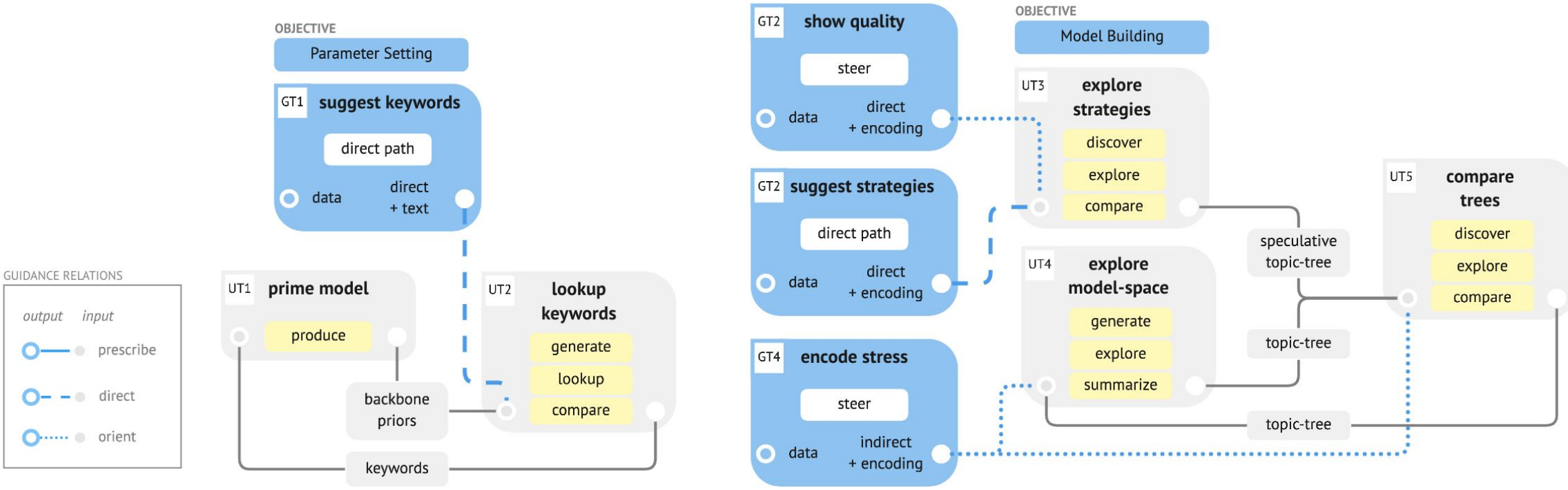
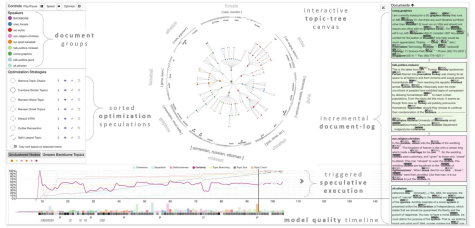


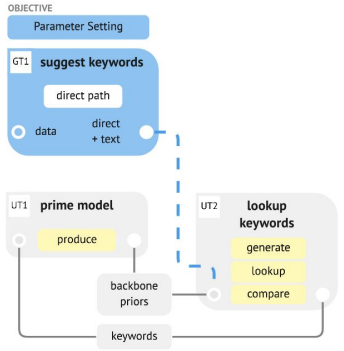


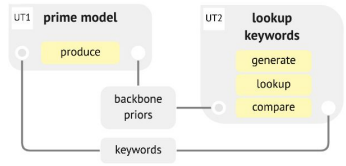
Case studies
Topic-Tree

Prescribing *Directing* *No guidance*

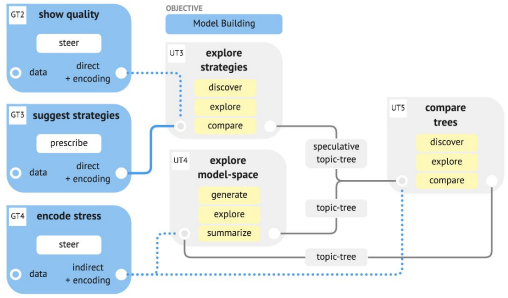
Objective

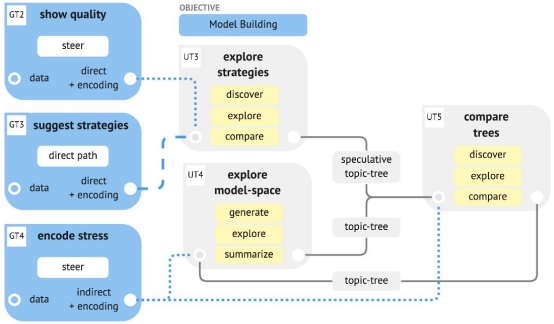
Parameter Setting

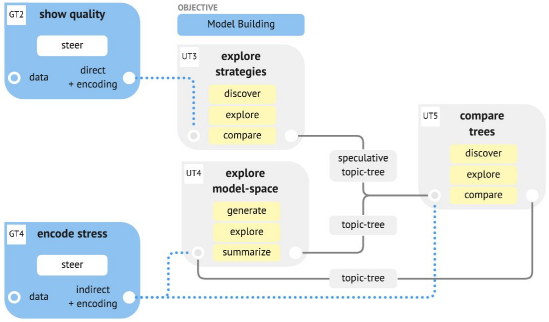




Model Building







Case studies
Topic-Tree

Prescribing 3

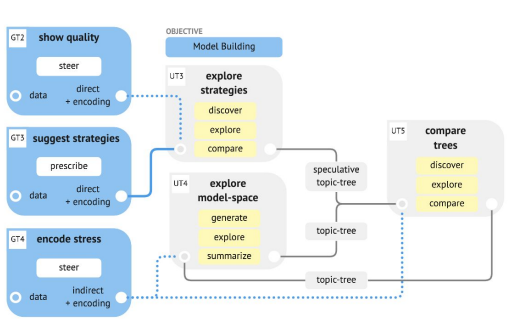
Directing 1

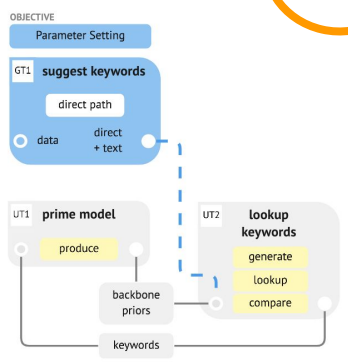
No guidance 2

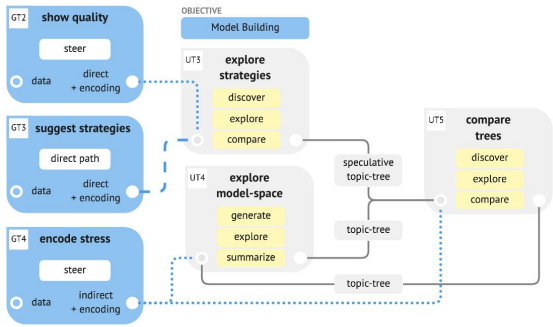
Objective

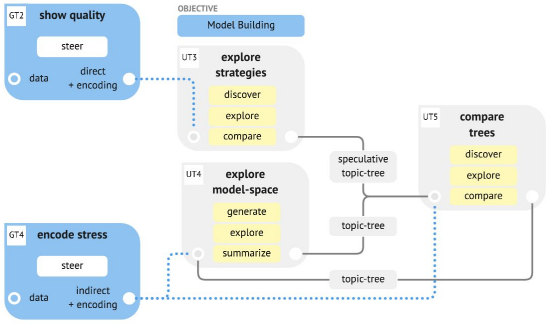
Parameter Setting

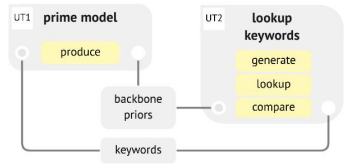
Model Building











Users consistently choose directing guidance over no guidance, followed by prescriptive guidance, as giving the best results.

Conclusion

- We have proposed a high-level model of guidance
- We have proposed the low-level model of perspective change
- We have proposed the concept of guidance tasks and a typology for them
- We have shown the applicability of guidance tasks in the analysis of mixed-initiative systems

Thanks!

EUROVIS 2022

A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

I. Pérez-Messina, D. Ceneda, M. El-Assady, S. Miksch and F. Sperrle

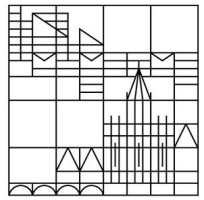
Guided VA

ETH AI CENTER

TU WIEN

VAST

Universität Konstanz



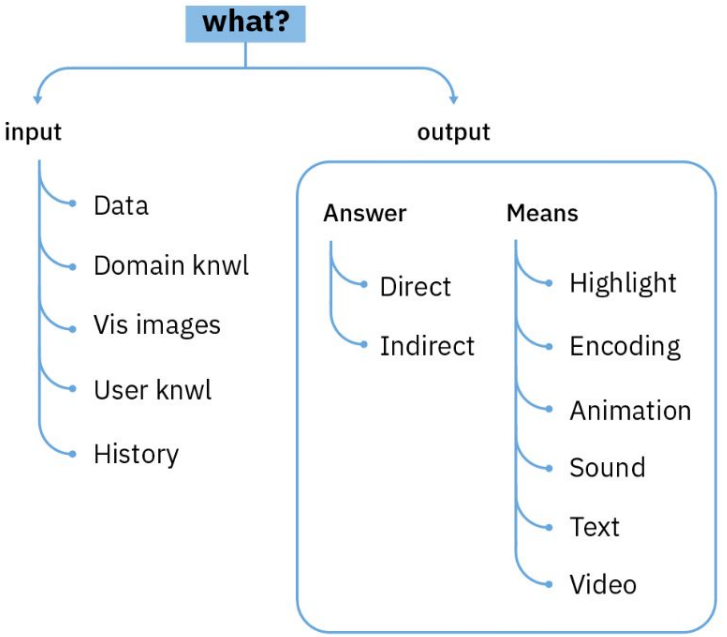
Takeouts

- There are guidance tasks
- Guidance tasks affect and change user tasks
- We can generalize results from mixed-initiative VA systems using guidance task analysis

A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

What?

Receives information from user tasks and provides an answer to the knowledge gap to user tasks.

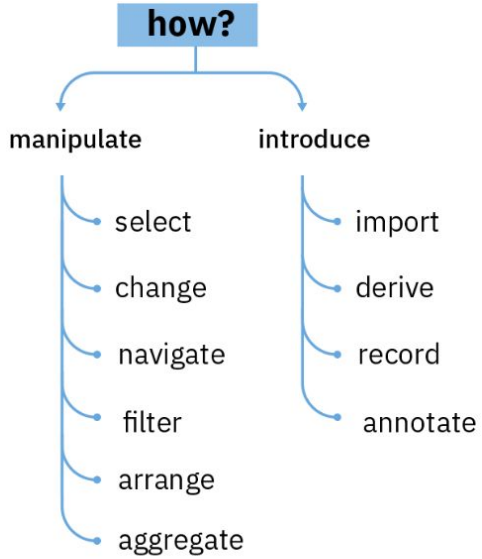


A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

How?

Abstract operation that is provided as guidance

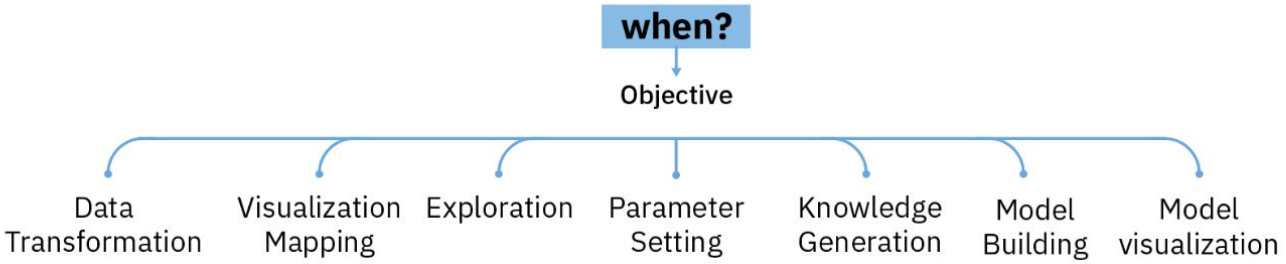
Taken explicitly from Brehmer & Munzner, 2013



A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

When?

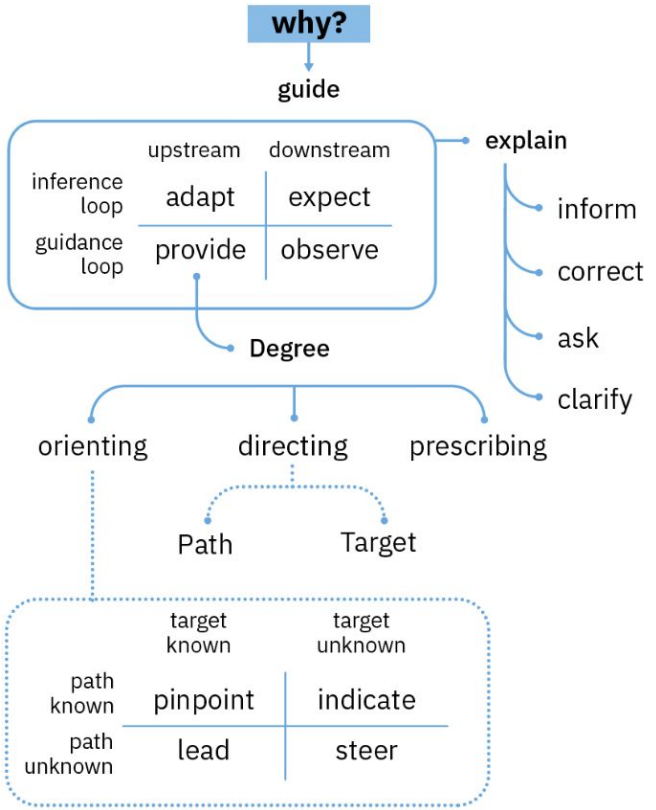
A global dimension that affects both user and guidance tasks (both must share the same **Objective** to be effectively connected)



A Typology of Guidance Tasks in Mixed-Initiative Visual Analytics Environments

Why?

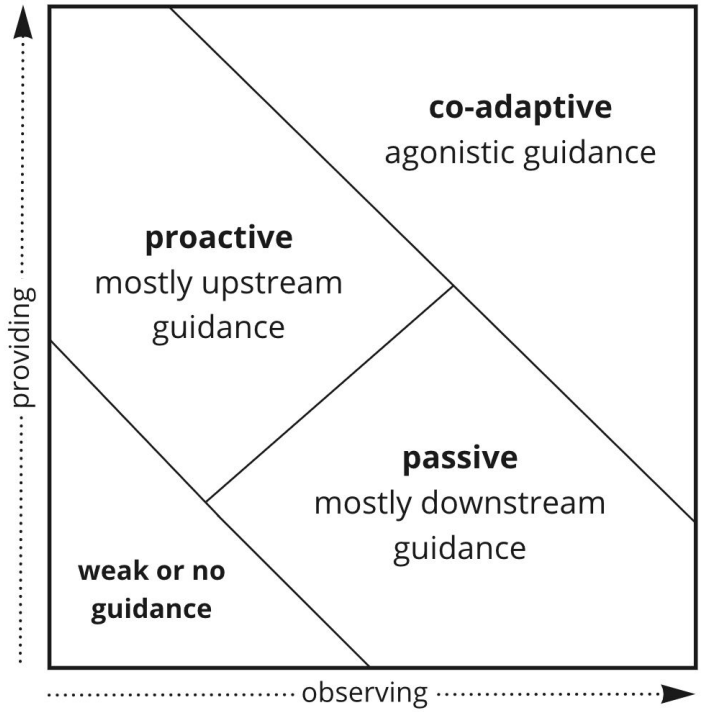
- Guide
  Divided into the 4 blocks of the Guided KGM (+Explain)
- Provide
  Divided into the 3 guidance degrees (subsequently divided into subdegrees)



Guidance Phase Space

Guided VA System can be divided into:

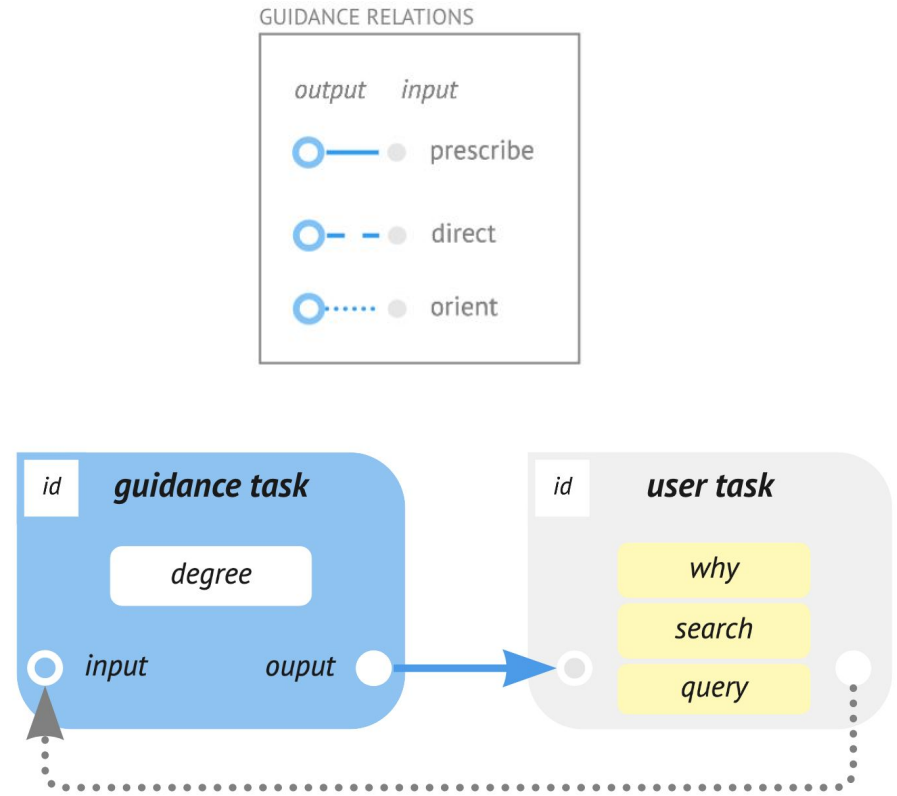
- Weak or no guidance
- Passive
- Proactive
- Co-adaptive



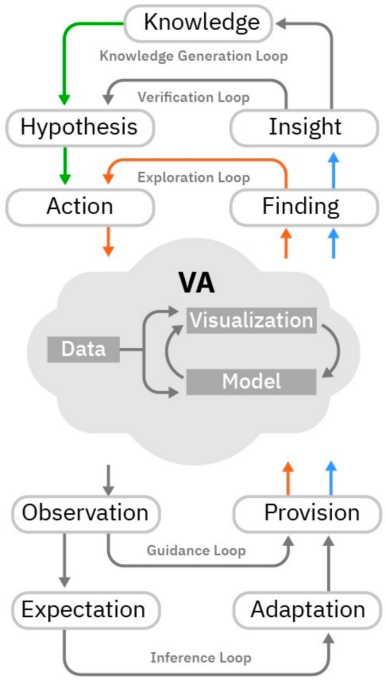
Using the typology

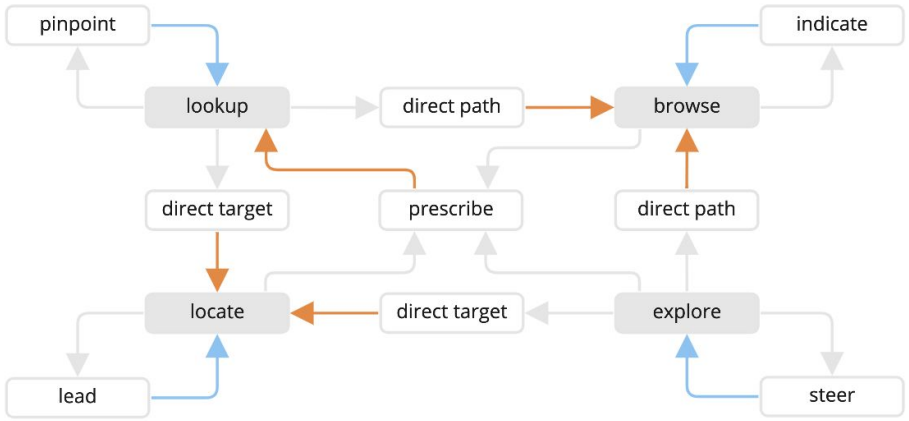
Composition rules

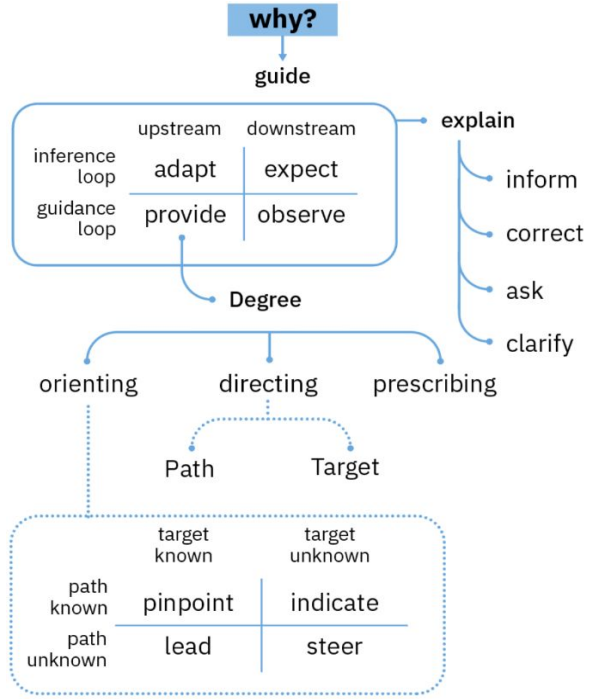
1. UTs and GTs are first described independently of one another.
2. UTs and GTs are assigned to analytical objectives.
3. Each GT must target at least one UT.
4. A targeting relation can be *observing*, *providing*, or *co-adaptive*, indicating the direction of the information flow.
5. *Produce* tasks may only be targeted by *observing* relations.



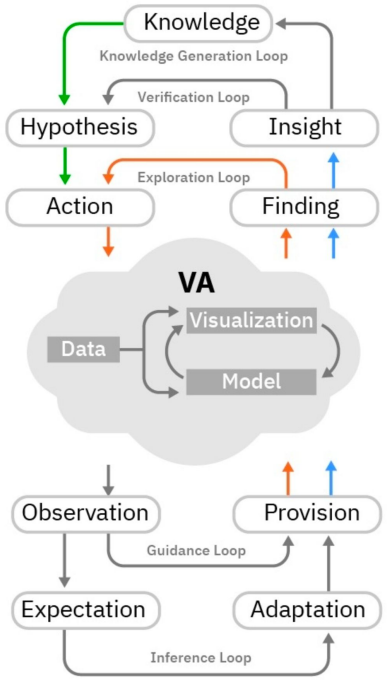
What do a Typology, a Model of Knowledge Generation and a Task Schema have in common?

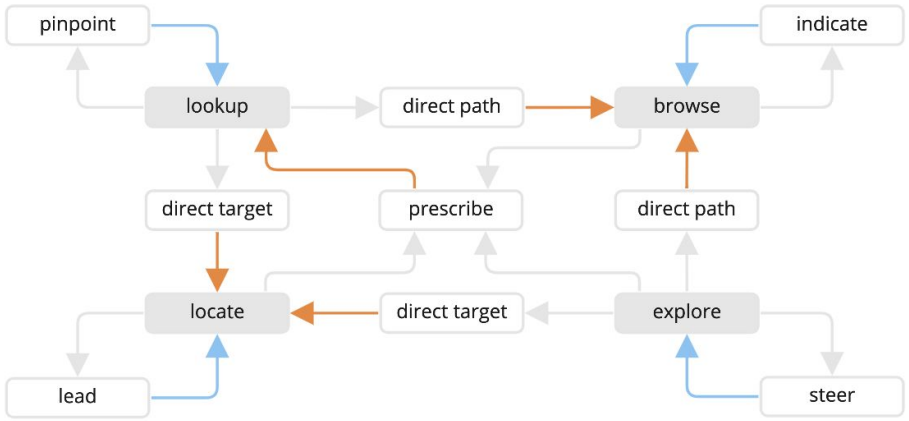


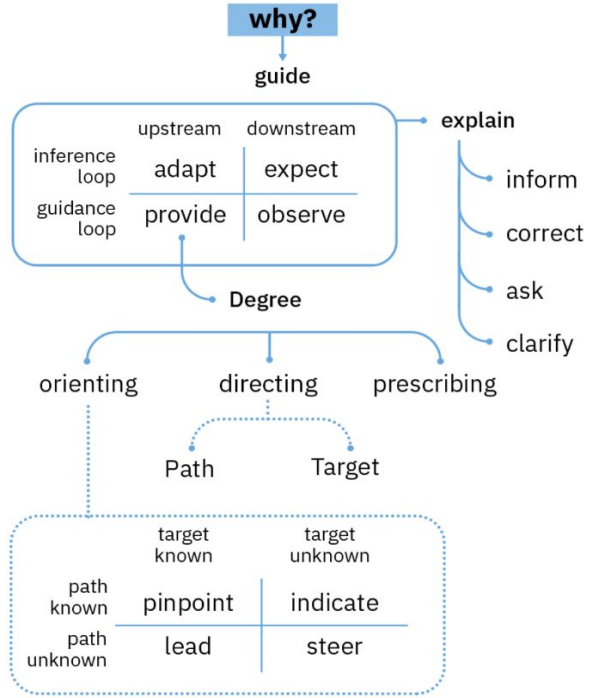




What do a Typology, a Model of Knowledge Generation and a Task Schema have in common?







perspective change

Team

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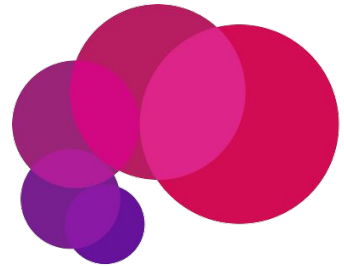

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