

# The Human User in Progressive Visual Analytics

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## Abstract

The amount of generated and analyzed data is ever increasing, and processing such large data sets can take too long in situations where time-to-decision or fluid data exploration are critical. Progressive visual analytics (PVA) has recently emerged as a potential solution that allows users to analyze intermediary results during the computation without waiting for the computation to complete. However, there has been limited consideration on how these techniques impact the user. Based on discussions from a Dagstuhl seminar held in October 2018, this paper characterizes PVA users by their common roles, their main tasks, and their distinct focus of analysis. It further discusses cognitive biases that play a particular role in PVA. This work will help PVA visualization designers in devising systems that are tailored for their specific target users and their characteristics.

## CCS Concepts

• **Human-centered computing** → *Visual analytics*; • **Social and professional topics** → *User characteristics*;

## 1. Introduction

Progressive Visual Analytics (PVA) has recently emerged as an effective approach for the interactive visual analysis of big data. Instead of processing a whole dataset at once, PVA processes datasets incrementally (i.e., one data chunk at a time; e.g., [Fis11]) or iteratively (i.e., one computational step at a time; e.g., [PLvdM\*17]). In this way, PVA generates a stream of in-progress results long before the dataset is fully processed. Through these intermediate results, progressive computations become observable, sometimes also controllable (e.g., pause, resume, stop [SPG14]) or even steerable (e.g. through data selection or re-parametrization [BEF17]) by a user during their execution. This newfound power over running computations can be leveraged by a user in various ways – from pinpointing areas of interest in large datasets all the way to rapidly cycling through possible computational methods and parameters.

However, current literature on the topic of PVA is mainly concerned with technical considerations [KCL\*17, FP16] and requirements [ASSS18, TKBH17, MPG\*14] for providing PVA. Yet in the context of visual analytics, technical and engineering considerations are only one side of the equation, which involves the users with their domain knowledge and common sense just as much as the system itself. While several PVA systems have meanwhile been implemented and discussed, the “human user in the progressive analysis loop” remains unexamined, resulting in unclear user objectives and tasks. This lack of a fundamental understanding of the

human user makes it in turn difficult to take the user in PVA scenarios properly into account – from performing systematic user requirements analyses to conducting methodical user evaluations.

This paper provides a structured summary and extension of discussions on the role of the human user in PVA from a Dagstuhl seminar held in October 2018 [FFNS18]. Its goal is to facilitate an understanding about how and when a PVA system can be useful and how it should be geared to address different user needs. This starts with the identification of common PVA user roles from which we derive analytic tasks and foci. In addition, biases are discussed that can result from using PVA. Table 1 provides an overview of the resulting characterization of PVA users. Its possible uses include:

- establishing user needs for tailoring PVA solutions to prospective user groups,
- configuring PVA workflows with adequate methods and tailored visual detail to support their tasks and analytic focus, and
- evaluating PVA systems considering potential biases.

**Table 1:** Overview of our characterization of PVA users

<b>Roles</b>	R1: Observer	R2: Searcher	R3: Explorer
<b>Tasks</b>	T1: Ascertain, T2: Reason, T3: Understand	T4: Analyze, T5: Refine, T6: Compare	T7: Overview, T8: Further, T9: What-If
<b>Focus</b>	F1: Data Space, F2: Algorithmic Space		
<b>Biases</b>	B1: Confirmation, B2: Illusion, B3: Unnecessary waiting, B4: Misjudging uncertainties		

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## 2. Who is looking? – User Roles in PVA

In terms of user roles, non-progressive VA relies on a fundamental distinction between the *monitor* who observes the analytic output, the *analyst* who look at selected data in depth, and the *modeler* who explores and tweaks the underlying computational methods [WMC15]. While our classification of user roles for PVA reflects this subdivision to some degree, the meaning of each role, its common activities and requirements are tied to quite different concerns as they relate to an ongoing analysis with in-progress results. These concerns are detailed in the following.

**R1: The Progressive Observer.** The Observer’s main interest is in the output of a progressive process, often without having knowledge of that process or PVA as an underlying concept. Thus, the Observer mainly wants to stay informed about the state of the computation, especially what was computed so far. On top of that, Observers might also monitor the running computation to better understand its inner workings, e.g., to ascertain the provenance of a result. An Observer’s expectation of the underlying PVA process is that of a smoothly converging output that arrives at a predictable end. The mental analogy of a “loading process” probably describes this expectation best. To support an Observer in using PVA without an extra learning curve for understanding its progressiveness, a PVA system can meet these expectations by the following means:

- Use established metaphors and familiar abstractions, e.g., that of a progressively loading online map, as it has already been showcased for large graph visualization [NPL\*15].
- Reduce visual complexity, fluctuations, jumps, flickering or any other indication of the underlying process not running smoothly and predictably – in particular if these are induced by external influences (garbage collection, memory swapping, etc.).
- Maintain the users’ mental map by introducing anchors [BEF17] or slowing down fast computations [VLCM14].

**R2: The Progressive Searcher.** The Searcher’s main interest is in using PVA for quickly finding an answer to a concrete question, or a solution to a particular problem within a large amount of data. To that end, the Searcher usually comes with a specific, run-time intensive query whose output will inform a time-critical decision that should be made as soon as reasonably trustworthy intermediate results are available. Note that this query is not confined to the data space, but can also entail to find, for example, suitable parameter settings. Searchers use PVA mainly for terminating processes mid-run in an informed manner – either by dismissing erroneous queries early on or by approving an already good-enough result. Both of these effectively speed-up the overall search. As such, a Searcher’s expectation of the underlying PVA is that of a step-wise process that produces constantly updated results and that can be terminated at any time. To facilitate the needs of a Searcher, a PVA system should employ the following means:

- Reflect – maybe even emphasize – any fluctuations, jumps, and other indications of the underlying process to make the user aware of issues with the query or model.
- Indicate uncertainty in a domain-specific and visual manner that allows judging the reliability of the intermediate results [AS17].
- Provide the possibility to parallelize queries or model runs, yielding an ensemble of progressively refining outputs that can be judged for their agreement or disagreement [Pol06].

**R3: The Progressive Explorer.** The Explorer’s main interest in PVA is for its flexible, steerable nature that allows adjusting an underlying computational process while it is running. It is often not a single result in which the Explorer is interested, but rather in gaining a comprehensive understanding of data and process. Hence, Explorers use the intermediate results of PVA to orient themselves and to decide in which direction to steer their “tour” through the data or parameter space, swiftly adjusting views and runtime constraints on the fly. Explorers can also aim to interactively pre-configure a PVA application for other users, such as Observers. Their expectation of PVA is that of an open, malleable process that can be redirected, reparametrized, reprioritized, and interactively perturbed. Explorers are aware of the progressive nature of the underlying process, as well as of the fluctuations and discontinuities their interactive adjustments introduce into that process. In fact, it is often these repercussions of their actions that they are interested in, as these may reflect hidden properties of data or process. To support such an involved use, PVA systems should offer means like:

- Expose all details and parameters of the PVA system to the user and make them adjustable on the fly.
- Incorporate statistics over the outputs and the process to provide a fixed, global view of the underlying process while the user quickly switches between visualizations or parameter settings.
- Allow possible changes in a What-If scenario that allows the user to test alternatives and compare their results later [AME11].

It is important to note that users can switch roles during a PVA session – e.g., from a searcher wanting to run a quick progressive query to an explorer, if that running query does not report back sensible intermediate results and he or she explores different parameter settings on the fly to “help the query along”. When designing PVA systems, attention should be paid to manage such switches so as not to confuse user roles while still making it as seamless as possible.

## 3. What are they looking for? – User Tasks in PVA

While a PVA approach can in principle support user tasks that are ascribable to those from the VA literature (e.g. [BM13, SSS\*14]), the strong influence of the progression on a user’s workflow can result in modifications that range from an expansion of the task scope to the attribution of a different semantic. The coupling between understanding the data (e.g. compare results of analysis, explore the data overview) and understanding the underlying progressive process (e.g. comparison between partial results, evaluation of uncertainty of the progression, exploration of a succession of partial results) motivates reformulation of these tasks in a way in which the progressive nature is not only taken into account, but becomes a primary concern of the analysis. In the following, we give a set of characteristic tasks for the different PVA user roles.

### 3.1. The Observer’s Analytic Tasks

Although the Observer’s role in PVA is typically passive, they still have expectations and analysis goals. In a broad sense, these relate to the aspects of monitoring the overall progression, as well as tracking individual patterns, which are also important tasks in streaming data scenarios [ROKF11]. Specifically, we identify that an Observer would use PVA to:

**T1: Ascertain suitable quality and quantity** of incoming data or computation results for subsequent analysis steps. Particularly in time-critical situations, where enough data of reasonable certainty needs to be available quickly, monitoring the sequence of progressive results helps confirming such scenario-dependent constraints.

**T2: Reason about large information spaces progressively** as complex datasets, computation results, or visualizations are incrementally updated. This progressive reasoning allows for forming and keeping a train of thought alongside the running progression, instead of being confronted with the end result.

**T3: Understand an algorithm and its inner workings** by observing its output and internal state as it runs. This helps to ensure the provenance of computational results, which ultimately builds trust in the otherwise hidden computational part of the analysis.

### 3.2. The Searcher's Analytic Tasks

Searchers may perform all of the Observers' tasks to monitor the progress of their search. In addition, they actively influence the progression through their queries and adjustments, which requires carrying out additional tasks. As the Searchers' analyses involve a specific question to be answered, their tasks reflect the notion of a sequence of coupled actions and reactions in the sense of a dialogue between analyst and progressive process, as put forth by Turky et al. [TKBH17]. We list three common tasks for the Searcher:

**T4: Analyze an approximation of the result** as one may not be able to wait for the arrival of the final result. This analysis is done with the explicit knowledge that the analyzed result is uncertain and that the actual final result may differ.

**T5: Refine the search space** based on the intermediate results provided by the progression, so as to make the progressive results more meaningful by targeting a given parameter or data subspace of interest. This task aims to specify a search objective in a number of quick, iterative steps based on early outcomes of the progression.

**T6: Compare different executions of the computation** to analyze the effects of different parameter settings or input data on a computational method, so as to establish its robustness and to identify the corner cases in which it does not work well.

### 3.3. The Explorer's Analytic Tasks

Again, the Explorers must be able to perform all the tasks of the Observers and the Searchers. But as they also need to actively steer the PVA and interact heavily with the underlying progressive process [MvWvL99], they also need support for the following tasks:

**T7: Gain an overview of a large information space.** Often the Explorers deal with data or parameter spaces for the first time and need to get a quick glance at the big picture to orient themselves, before steering the analysis in a particular direction. This usually involves a progression of samples of the full information space.

**T8: Identify possibilities for furthering the computation** by integrating the user's tacit knowledge or preferences at different stages of the ongoing computation. This relates, for example, to influencing an otherwise unsupervised algorithm, for example by interactively reassigning data items to more meaningful clusters.

**T9: Investigate alternative scenarios** by branching off the analysis into What-If scenarios, pursuing them in parallel, only to merge their results or simply decide for the better one in the end. Because of the progression, this can actually be done mid-computation.

Note that the focus of this list of tasks lies on the progressive analysis itself. On top of that, additional management tasks to deal with the progressive process have to be carried out by the user – e.g., running, pausing, terminating the computation, or increasing, decreasing the step size/chunk size.

## 4. Where are they looking at? – User Focus in PVA

Due to long execution times often inherent in non-progressive VA, it is commonly separated into the planning of an analysis in the *algorithm space* by choosing and configuring the computational methods, models, and parameters – and into using and assessing a configured analysis workflow in the *data space* [YEB16]. This separation is so ingrained in current practices, that it is only explicitly mentioned in a few ambitious cases aiming to combine both, e.g., [KHS\*17, SJS\*19]. In PVA however, this distinction is no longer evident and users can and should switch seamlessly between investigating the data and adjusting the algorithm while the analysis runs. Yet because PVA increasingly blurs the lines between these two analytic foci, considering them explicitly for the design and evaluation of PVA systems becomes even more important. The following classification succinctly frames them for this purpose.

### 4.1. F1: Focus on the Data Space

When focusing on the data, analysts want to make use of PVA for analyzing their data without necessarily having to understand its internal working and the considerations behind it.

The simplest case is **Observing the Data Space** (R1) for being kept informed about an ongoing background process in the data space. This information includes, for example, the progression's aliveness and progress. A prime example for this kind of use is *visual sedimentation* [HVF13], which renders otherwise invisible data updates as a trickling stream of particles settling down into a preliminary result. This communicates the aliveness of the background process, the speed at which the data comes in, as well as the fact that the current visualization is not yet final.

In the case of **Searching the Data Space** (R2), the user wants to query a very large data set, but cannot wait for the timely and costly data retrieval computation to return the accurate results. One alternative is to run the user query on incremental samples of the data set instead of the entire data set [FPD\*12]. The intermediate results are progressively visualized together with a confidence range and an indicator of the relative progress (e.g., sampling rate).

When **Exploring the Data Space** (R3), the analyst makes use of PVA to provide an overview even of large information spaces that refines over time and enables early interaction, such as zooming into regions that seem particularly promising. This in turn can direct the progressive computation to the parts of the space that the user would like to explore further [PSWC17]. Such user interaction not only speeds up the computation by focusing it on the data subsets of interest, but also supports the user in gradually building a mental model of the data and forming hypotheses.

## 4.2. F2: Focus on the Algorithm Space

When focusing on the progressive process itself, analysts aim to trace and adjust the process, so as to provide an improved or better tailored progressive analysis.

When **Observing the Algorithm Space** (R1), the user aims first and foremost to gain an understanding of the inner workings of a computational process. Using modern hardware, it is possible to smoothly simulate the evolution of complex algorithms, and to observe for example the inner workings of a neural network, such as the dataflow between input, hidden layers, and output [SCS\*17].

In case of **Searching the Algorithm Space** (R2), the analyst wants to adjust parameter settings or swap out entire computational modules or models, and evaluate new algorithmic configurations by test-driving them on datasets with known ground truth. In this case, the user can run multiple executions of the same progressive computation using different parameter sets, compare their intermediate results, and successively terminate executions once it becomes obvious that they do not perform [ASSS18].

The case of **Exploring the Algorithm Space** (R3) is about browsing through and experimenting with the multitude of process behaviors as they result from different algorithm choices or parameters. In other cases, a user may want to explore the parameter space of a computation while it is running, as it is the case in interactive flooding simulations where different constellations of water influx and barriers are tested in What-If scenarios [WFR\*10].

## 5. What could possibly go wrong? – User Biases in PVA

One of the main characteristics of PVA is its ability to increase user involvement in visual data analysis. Yet the user introduces not only creativity, background knowledge, and past experiences in the analysis process, but also personal preferences and subjectivity of human judgement. One widely studied phenomena are cognitive biases in human reasoning [EBP83,DFP\*18], which is a systematic and involuntary way of how humans deviate from rational judgment, regardless of intelligence and domain expertise. Cognitive biases introduce a number of pitfalls into the PVA reasoning process of assessing intermediate results, which in turn can lead to inaccurate judgment and non-optimal decisions based on distorted perception. The following briefly outlines four such pitfalls, and provides some indication on how to counter them.

### B1: Using incomplete results to confirm a preferred hypothesis.

The incomplete and often fluctuating nature of intermediate results in PVA increases the likelihood for confirmation bias [Mah77], as a user has the possibility to subconsciously stop the computation once the output corresponds to a prior assumption. Even if the stream of intermediate results is not as clear-cut and also shows outputs that could be used to refute the hypothesis – human users tend not only to ignore evidence that rejects a believable conclusion (belief bias [EBP83]), but also to exaggerate the evidence supporting the preferred hypothesis (exaggerated expectation [WK85]).

### B2: Read something into incomplete results that is not there.

Additionally, a user could easily mistake artifacts of the progression for patterns in intermediary results. These patterns could, for example, be clusters or relationships between variables that do not

exist (clustering illusion [KT72], illusory correlation [CC69]). If such PVA artifacts occur frequently and the user is repeatedly exposed to similar illusory patterns during the progression, then the user is more likely to consider his false prediction as true (illusory truth effect [HGT77] and attentional bias [JPR\*10]).

**B3: Waiting for information irrelevant for the intended goal.** In PVA, users can easily get distracted by the constant influx of updated results and be paralyzed in their ability to make decisions. This traces back to the information bias [BBH88], which leads users into believing that more information also leads to more informed decisions – even when this information is not relevant to that decision. Interestingly, the opposite is often true, as humans typically make better decisions with less information [Bar00].

**B4: Misjudging the uncertainty of intermediate results.** Before making a decision based on these intermediate results, the user must adequately judge the uncertainty of the depicted results. Yet if, for example, the progression exhibits fluctuations in the results and generates seemingly ambiguous outcomes, the user might not trust an otherwise fine approximation (ambiguity effect [RB90]). Even when explicitly measuring and showing the result's uncertainty, the user is still likely to disregard it (neglect of probability bias [Sun02]). On the other end of the spectrum, a user might place unwarranted trust in any result that resembles the first initial results shown, due to the anchoring effect [FB11], which reports a disproportionate influence of a “first impression” on the user's decision.

The field of “de-biasing” decision making [SMP15] is a rather recent research domain, which has brought forth ideas ranging from forced breaks for reflection to incentivizing objective decisions. As for PVA, biases are more likely to influence time-critical analyses under high uncertainty based on immature results. One way to counter them is to speed up the computation, so as to reach better substantiated results in the same time. Alternatively, such a speed-up can also be used to follow multiple, possibly competing analysis threads at once, which is known as “analysis of competing hypotheses” [HJ99]. If no such speed-up can be achieved, collaborative analysis involving multiple analysts with different backgrounds has also been shown to alleviate individual biases [CBP\*08].

## 6. Conclusion

The user characterization presented in this paper not only demonstrates the versatility of PVA, but also exposes the diverse human factors that need to be taken into account when designing PVA systems. This characterization will help designing PVA systems that are better tailored for the human users, based on the role they would like to attain and the tasks they would like to accomplish. In particular, the discussed roles, tasks, foci, and biases can help to ensure that newly devised PVA systems provide informative but not misleading information, particularly when users reason about and make decisions on incomplete intermediate results.

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