Transactional Panorama: A Conceptual Framework for User Perception in Analytical Visual Interfaces

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ABSTRACT

Many tools empower analysts and data scientists to consume analysis results in a visual interface. When the underlying data changes, these results need to be updated, but this update can take a long time—all while the user continues to explore the results. Tools can either (i) hide away results that haven't been updated, hindering exploration; (ii) make the updated results immediately available to the user (on the same screen as old results), leading to confusion and incorrect insights; or (iii) present old—and therefore stale—results to the user during the update. To help users reason about these options and others, and make appropriate trade-offs, we introduce Transactional Panorama, a formal framework that adopts transactions to jointly model the system refreshing the analysis results and the user interacting with them. We introduce three key properties that are important for user perception in this context: visibility (allowing users to continuously explore results), consistency (ensuring that results presented are from the same version of the data), and monotonicity (making sure that results don't "go back in time"). Within transactional panorama, we characterize all feasible property combinations, design new mechanisms (that we call *lenses*) for presenting analysis results to the user while preserving a given property combination, formally prove their relative orderings for various performance criteria, and discuss their use cases. We propose novel algorithms to preserve each property combination and efficiently present fresh analysis results. We implement our framework into a popular, open-source BI tool, illustrate the relative performance implications of different lenses, and demonstrate the benefits of the novel lenses and our optimizations.

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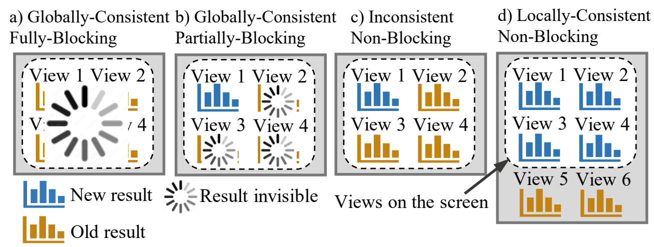


Figure 1: Visual examples of different lenses for refreshing views in a dashboard

1 INTRODUCTION

Many data-centric tools empower a user to visually organize, present, and consume multiple data analysis results within a single interface, such as a dashboard. Each such analysis result is represented on this interface as a scalar value, table, or visualization, and is computed using the source data or other analysis results, in turn, as *views*. This pattern appears in a variety of contexts:

Visual analytics or Business Intelligence (BI) tools, like Tableau [12] or PowerBI [8], empower a user to embed visualizations on a dashboard, each via a SQL query on an underlying database;

Spreadsheet tools, such as Microsoft Excel [6] and Google Sheets [2], allow a user to add derived computation in the form of spreadsheet formulae, visualizations, and pivot tables;

Data application builder tools, such as Streamlit [10], Plotly [7], and Redash [9], enable a user to efficiently develop interactive dashboards, employing computation done in Python UDFs and pandas dataframe functions, and SQL; and

Monitoring and observability tools, such as Datadog [1], Kibana [4], and Grafana [3], empower a user to make sense of their telemetry data and logs via a combination of automatically defined and customizable dashboard widgets.

In all of these contexts, there is *a network of views defined on underlying data, each of which is then visualized on an interface.* These views and the corresponding visualizations often need to be refreshed when the source data is modified. For example, a dashboard in a BI tool is refreshed with respect to regular changes to the underlying database tables (e.g., new batches of data). However, this refresh is rarely instantaneous, especially on large datasets. This represents a challenge, since the user is continuously exploring the visualizations during the refresh. On the one hand, refreshing visualizations arbitrarily can be jarring to the user, since different visualizations on the screen may be in different stages of being refreshed. On the other hand, not refreshing them in a timely manner can lead to

Table 1: Properties maintained by existing tools

Lens name	Example Tools	Monotonicity	Visibility	Consistency
Globally-Consistent Fully-Blocking (GCFB)	MS Excel [6] Libre Calc [5] Tableau [12]	Yes	No	Yes
Globally-Consistent Partially-Blocking (GCPB)	Power BI [8] Superset [11] Dataspread [16]	Yes	No	Yes
Inconsistently Non-Blocking (ICNB)	Google Sheets [2]	Yes	Yes	No

stale results. The question we explore is: ***How do we allow users to continuously explore results in a visual interface, while ensuring that the results are not confusing or stale?***

Unfortunately, existing tools make fixed, and somewhat arbitrary decisions on how to address this question. For example, Excel [6], Calc [5], and Tableau [12] block the user from exploring the interface until all of the views are refreshed (Figure 1a). Other tools, like PowerBI [8], Superset [11], and Dataspread [16], improve on this approach by hiding (or greying) away any views that have not yet been refreshed, while still letting the user explore the other up-to-date views (Figure 1b). Yet other tools, like Google Sheets [2], opt for not hiding any views, and instead just progressively make them available as they are refreshed—this approach has the downside of different results on the screen being in different stages of being refreshed, leading to incorrect insights (Figure 1c).

Transactional Panorama and Underlying Properties. In this paper, we introduce *transactional panorama*[1], a formal framework that enables users and system designers to reason about the aforementioned question in a more principled manner. We adopt transactions to jointly model the system concurrently updating visualizations, with the user consuming these visualizations, over time and space (i.e., across screens). To the best of our knowledge, *transactional panorama is the first framework that leverages transactions to reason about correct user perception in visual interfaces.* In this setting, we define three key desirable properties *monotonicity*, *visibility*, and *consistency*, which we call the *MVC properties.* Monotonicity guarantees that if a user reads the result for a view, any subsequent read will always return the same or more recent result (i.e., monotonic read [33]) so that results never go "back in time". Visibility guarantees that the user can always explore the result of any visualization on the screen—instead of them being greyed out. Consistency guarantees that the results displayed on the screen should be consistent with the same snapshot of source data [24, 43]—enabling correct derivation of relationships between results on the same screen.

Concrete Property Combinations via Lenses. There are various mechanisms we can use to present results to the user in a visual interface, resulting in concrete selections for the aforementioned properties, that we call *lenses*[2]. Consider our examples of existing systems (Figure 1a–c); we list the corresponding three lenses in Table 1—GCFB, GCPB, and ICNB (the acronyms will be explained later). While GCFB and GCPB opt for monotonicity and consistency, instead of visibility, ICNB opts for monotonicity and visibility, but not consistency. In this work, we study the feasibility of different property combinations and lenses, and characterize their performance trade-offs. In particular, we explore the trade-off between

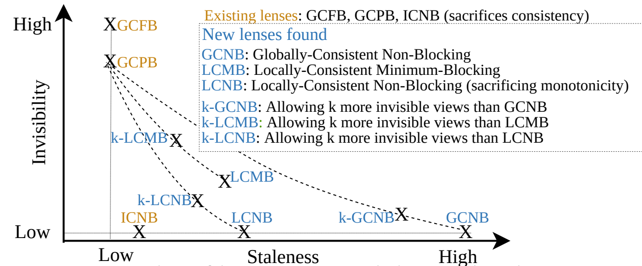


Figure 2: Trade-off between invisibility and staleness across different lenses

invisibility, i.e., the duration when the user is unable to interact with visualizations, and *staleness*, i.e., the duration when visualizations displayed to the user have not been refreshed, as shown in Figure 2. For example, GCFB blocks the user from exploring the interface until all of the new results are computed, so it has high invisibility. But GCFB also has zero staleness since it does not present stale results. On the other hand GCPB reduces invisibility (vs. GCFB) by presenting the newly computed results to the user whenever available while also not showing stale results. ICNB, which sacrifices consistency, has higher staleness because the user can read stale results, but none of the views shown are invisible, i.e., visualizations that are greyed out.

Novel Property Combinations: Exploring the Trade-off. As we also show in Figure 2 (in green), we discover a number of novel lenses, resulting in new property combinations and associated performance implications. We introduce three new lenses: Globally-Consistent Non-Blocking (GCNB), Locally-Consistent Non-Blocking (LCNB), and Locally-Consistent Minimum-Blocking (LCMB), none of which are dominated by the three existing lenses. For example, LCNB always allows the user to inspect the results of any visualizations (i.e., preserving visibility), and refreshes the visualizations on the screen when all of their new results are computed (i.e., preserving consistency). Figure 1d shows an example of LCNB, where the user can quickly read the new results on the screen (i.e., $View_{1-4}$) without waiting for computing the new results that are not on the current screen (i.e., $View_{5-6}$). LCNB can be used when a user wants to always see and interact with consistent results on the screen. However, as we prove later, LCNB needs to sacrifice monotonicity when the user explores different visualizations (e.g., by scrolling). In fact, we demonstrate one can achieve both consistency and visibility simultaneously only by either sacrificing monotonicity or suffering from high staleness. For the aforementioned new lenses, we further introduce k-relaxed variants (i.e., k-GCNB, k-LCNB, and k-LCMB), where k represents the number of additional invisible views allowed for each lens.

Usage Scenarios. This suite of lenses allow a user or a system designer to determine their desired properties and gracefully explore the trade-off between staleness and invisibility. Current tools, while enabling users to customize their dashboards extensively (in terms of the placement of visualizations and selection of visualization queries and encodings), make fixed choices in this regard. A user has no say in how results are refreshed and presented, and a system designer opts for whatever is easiest. The transactional panorama framework is intended to address this gap. From an end-user standpoint, they may be able to make appropriate performance trade-offs via various customization knobs. A system designer may similarly

[1]We call this framework as such because it involves adapting transactions to a problem of fidelity across various viewpoints (screens) over space and time, i.e., a panorama.
[2]These are called lenses since they capture various instantiations of our transactional panorama framework.

be able to make appropriate selections during tool design, with end-users and use-cases in mind.

Translating to Practice: Challenges. Translating our transactional panorama framework to practice in real data analysis and BI systems requires addressing several challenges:

(1) In a visual interface, the user does not explicitly submit transactions as in traditional systems, but reads the views by looking at the screen. In addition, the user can read different subsets of views by scrolling to different screens. Therefore, a challenge is to adapt transactions to model user behavior, an aspect not considered in classical transaction processing literature.

(2) In a visual interface, the user may want to quickly read new results for some views before the system computes all of the new results. If we model an update along with refreshing the related views as a transaction (to preserve consistency), the user essentially wants to read the results of an *uncommitted transaction*. The MVC properties for reading uncommitted results are not considered by traditional systems and needs to be defined in our model.

(3) Finally, instantiating transactional panorama requires designing new algorithms for efficiently maintaining different property combinations for different lenses while reducing invisibility and staleness. Traditional concurrency control protocols, such as 2PL or OCC [17], do not apply here because they do not consider maintaining consistency on uncommitted results and the other user-facing properties, monotonicity and visibility.

Summary of Contributions. We address these challenges as part of transactional panorama and make the following contributions:

- We present the transactional panorama model in Section 2. We model reads and writes on the views as operations within transactions and introduce a special read-only transaction to model a user's behavior of reading the views on the screen. We define the MVC properties and use a series of theorems to exhaustingly explore the possible property combinations. We formally order different lenses based on invisibility and staleness, and provide guidance for selecting the right lens for specific use cases.
- We design efficient algorithms for maintaining properties for lenses in Section 3, and propose optimizations to reduce invisibility and staleness while refreshing analysis results in Section 4.
- We implement transactional panorama within Apache Superset, a popular open-source BI tool [11], in Section 5. We perform extensive experiments to characterize the relative benefits of different lenses on various workloads, demonstrate the benefits of the new lenses, and show the performance benefit of our optimizations on reducing invisibility and staleness compared to the baselines—by up to **70%** and **75%**, respectively—in Section 6.

2 TRANSACTIONAL PANORAMA MODEL

We present our transactional panorama model in this section. Due to space limitations, we had to omit the discussion for selecting appropriate lenses for specific use cases and a number of extensions to our framework; these can be found in our technical report [13].

2.1 Preliminaries

View and view graph. In our context, we define a *view* to represent arbitrary computation, expressed in any manner, including

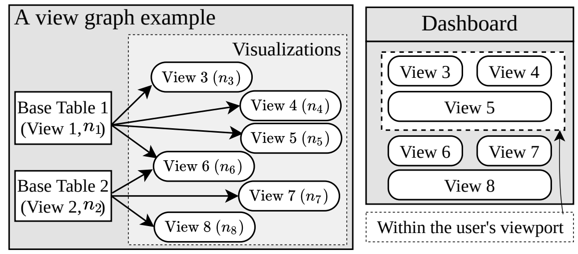


Figure 3: An example of a dashboard and its view graph

SQL, pandas dataframe expressions, spreadsheet formulae, or UDFs, taking other views and/or source data as input. A view graph is a directed acyclic graph (DAG) that captures the dependencies across views and source data, both represented as nodes in the DAG. Specifically, if a view n_i takes another view or source data n_j as input, we add an edge: $n_j \rightarrow n_i$. The *dependents* of n_j are defined as the views that are reachable from n_j in the view graph. For simplicity, we regard the source data as a special type of view that performs an identity function over the source data. Figure 3 shows an example of a view graph for visualizations in a dashboard, where the source data are database tables and each view is defined by a SQL statement. There are two base tables: Base Table 1 and 2, also regarded as View 1 and 2, respectively. We use n_k to represent View k. View 3-6 (denoted n_{3-6}) and View 6-8 (denoted n_{6-8}) are the dependents of n_1 and n_2, respectively. They define the content for the visualizations in this dashboard.

View result and viewport. A *view result* represents the output of a view given a version of the source data and the definition of the view graph. This view result is rendered on the dashboard as a visualization (this includes visualizations of tables or even single values). In certain settings, a view definition may itself be editable and rendered as part of the dashboard (e.g., as a filter). For the following discussion, we assume view definitions are not editable or rendered. The discussion for reading and modifying a view definition is in the technical report [13].

A dashboard may include many visualizations that cannot fit into a single screen. The rectangular area on the screen a user is currently looking at is the *viewport*. In Figure 3, the viewport includes visualizations for views n_{3-5}. A user can change the viewport to explore different parts of a view graph.

Reading and writing a view, and view state. We model the user inspecting a visualization in the viewport as reading the corresponding view, which returns a *view state*. A view state is either a view result or a state that indicates the view result has not been computed yet (denoted as *under-computation*) and is usually materialized such that future reads coming from the user can reuse the materialized state. In Figure 3, we need to materialize the view states for n_{3-8} to support future reads by the user.

There are two types of writes in transactional panorama: *input writes* and *triggered writes*. An *input write* is from a user or an external system, and modifies the source data (e.g., new data inserted to a base table) or view graph definitions. The following discussion focuses on input writes to the source data. The case of processing modifications to the view graph definitions is in the technical report [13]. The input write will trigger additional writes, called *triggered writes*, which compute new results for the views that depend on the base views which were modified in the input

Table 2: Notation frequently used in this paper

Notations	Meanings
w^{t_i}	A write transaction that is created at timestamp t_i
r^{s_i}	A read transaction that is created at timestamp s_i
G^{t_i}	A version of the view graph created by w^{t_i}
n_k	A view in the view graph
$n_k^{t_i}$	A view result for n_k in G^{t_i}
$UC_k^{t_i}$	A state representing the view result $n_k^{t_i}$ is under computation
V^{t_i}	A set that stores the view results and UCs for the views in G^{t_i}
C_f	Consistency-fresh
C_m	Consistency-minimal
C_c	Consistency-committed

write. For example, modifying the base table n_1 in Figure 3 triggers computing new results for n_{3-6}.

2.2 Modeling the Interaction with a View Graph

We model a user's or an external system's interaction with a view graph as transactions, and logically associate each transaction with a unique timestamp that represents its submission time, with transactions being ordered by these timestamps. We focus on a single user setting as in most user-facing data analysis tools and discuss the multiple user setting in the technical report [13]. Our model has two types of transactions:

Write transaction. A write transaction is issued when a set of input writes on the view graph (e.g., modifications to a set of base tables) are submitted together to the system. A write transaction involves processing the input writes and recomputing the views that depend on the input writes. For example, in Figure 3 if n_1 is modified the write transaction will recompute n_{3-6}. The specific algorithm for maintaining the view graph and recomputing view results is orthogonal to our model, and, for example, can employ incremental view maintenance [14, 25, 35]. We focus on processing one write transaction at a time, which is typical in existing tools [6, 8, 11, 12], and discuss the case of multiple, simultaneous write transactions in the technical report [13].

Read transaction. Transactional panorama models a user inspecting visualizations in the viewport as a read transaction. For example, in Figure 3, the read transaction involves reading views n_{3-5}. A unique property of this read transaction is that it does not delay to wait for the requested view results to be computed. So the read transaction may return an under-computation state for a visualization if the view result has not been computed yet. If an under-computation state is returned, the user cannot inspect and interact with the visualization in the visual interface. To simulate the effect of the user "looking at" the viewport, our model assumes the system periodically issues new read transactions to pull view states. The user may read different parts of the view graph by changing the viewport while the system continues to process writes. The location of the user's viewport is known to the system throughout.

2.3 Formalization

We now introduce the aforementioned concepts in more detail and more formally. Table 2 summarizes the notation frequently used in this paper. The view graph is logically multi-versioned, where a new version of view graph $G^{t_i} = (E, N, V^{t_i})$ is instantiated by a write transaction with timestamp t_i (denoted as w^{t_i}). N represents the set of nodes (i.e., source data and views) in the graph and each edge $e = (n_{prec}, n_{dep}) \in E$ indicates that node n_{dep} has another node n_{prec} as input. V^{t_i} captures the view results and the under-computation states for the views in G^{t_i} and evolves as we process the write transaction w^{t_i}. At a given time, V^{t_i} may include: i) the view result for n_k that w^{t_i} has already finished computing — this view result is represented as $v_k^{t_i}$; ii) $\text{UC}_k^{t_i}$, which represents the state that w^{t_i} intends to compute the view result for n_k, but has not done it yet; and iii) the view result for n_k from the last version of view graph given that n_k will not be updated by w^{t_i}. Figure 4 shows an example of computing a new version of view graph for a write transaction w^{t_1} that modifies n_1 in Figure 3. We see that creating a new version of view graph logically replicates the view results of the last version of the view graph, and marks all of the view results to be computed as UCs (in gray). Each UC is replaced after the corresponding view result is computed (in blue). We guarantee that a new version of view graph is atomically seen by read transactions via our concurrency control protocol (to be discussed in Section 3). We call a version of view graph *committed* if its write transaction is committed; otherwise, this version is *uncommitted*. A write transaction is defined to be committed if the system has a) computed all of the new view results for the version of view graph created by this write transaction and b) updated a global variable that stores the timestamp of the recently committed graph. More details about the procedure for processing a write transaction and the management of the global variable are in Section 3.2. The initial version of the view graph is G^{t_0}, which is modified by a sequence of write transactions $W = \{w^{t_1}, \cdots, w^{t_n}\}$, where w^{t_i} is submitted before w^{t_j} if $t_i < t_j$.

We also have a sequence of read transactions $R = \{r^{s_1}, \cdots, r^{s_m}\}$, where r^{s_i} is submitted before r^{s_j} if $s_i < s_j$. Recall that each read transaction corresponds to a single viewport and all of the views in it. We refer to the view states returned by a read transaction r^{s_i} as H^{s_i}, which includes view results and/or UCs for the views in the viewport. If a read transaction returns a UC for a view, its corresponding visualization is marked as *invisible* in the dashboard. On the front end, this can be displayed in various ways: grayed out, a progress bar, a loading sign, etc. We use UC for $\text{UC}_k^{t_i}$ when k and t_i are clear from the context.

2.4 MVC Properties

We now formally define the so-called MVC properties for read transactions, motivated by user needs in analytical visual interfaces. First, the user consumes the view states returned by read transactions in order: i.e., they consume the view states of one read transaction before the next. Therefore, they expect to see *monotonically* newer states for each view, avoiding the confusion that the states seen "travel back in time". Second, in a user-facing dashboard, the notion of *visibility* helps ensure interactivity, as it means the user can continuously explore the view results of different visualizations without interruption, while the system processes write transactions. Finally, *consistency* helps ensure that insights derived from multiple visualizations on a viewport are computed from the same snapshot of source data [24, 37, 43]. We now describe each property in detail.

Monotonicity. Monotonicity means if a user reads a given version of a view result or UC for a view, any successive reads on the same view will return the same or more recent version of the view result or UC. Formally, monotonicity is defined as:

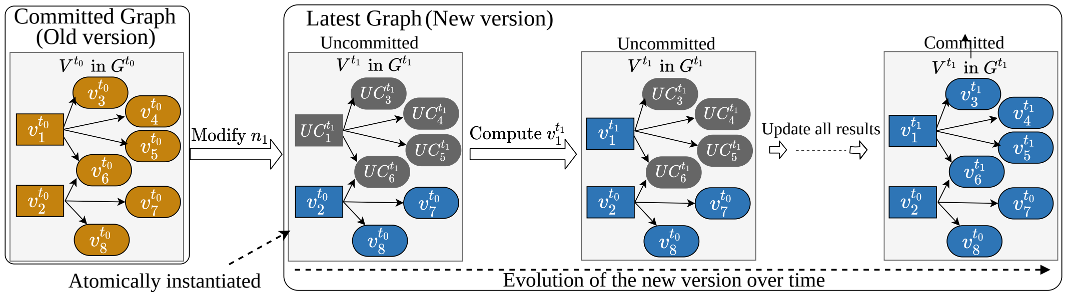


Figure 4: An example of creating a new version of view graph and computing the view result for each node

Definition 1 (Monotonicity). *A sequence of read transactions $R = \{r^{s_1}, \cdots, r^{s_m}\}$ maintains monotonicity if the following holds: for any view n_k read by any two transactions r^{s_i} and r^{s_j}, the timestamps of the returned states are t_p and t_q, respectively: $t_p \leq t_q$ if $s_i < s_j$.*

Visibility. This property says that for any view that is read by any read transaction, the system should not return an under-computation state, UC. Formally, visibility is defined as:

Definition 2 (Visibility). *A sequence of read transactions $R = \{r^{s_1}, \cdots, r^{s_m}\}$ maintains visibility if for the states H^{s_i} that are returned by any transaction r^{s_i}, we have $UC \notin H^{s_i}$.*

The user may also sacrifice visibility by opting for partial visibility, where they accept a controlled number of UCs as a trade-off for reading fresher view results, discussed next.

Consistency. In our setting, consistency means that the view states returned by each read transaction belongs to a single version of the view graph. Consistency is formally defined as:

Definition 3 (Consistency). *Let H^{s_i} be the view states returned by r^{s_i}. We say r^{s_i} maintains consistency if there exists a version of view graph $G^{t_j} = (E, N, V^{t_j})$ such that $t_j \leq s_i$ and $H^{s_i} \subseteq V^{t_j}$.*

Intuitively, $t_j \leq s_i$ requires that a user read a version created by the write transactions that happen before r^{s_i}. The condition $H^{s_i} \subseteq V^{t_j}$ guarantees that the view states returned belong to a single version of view graph. Consider a read transaction r^{s_1} that reads n_{3-5}. Say for G^{t_1} in Figure 3, we have computed $v_3^{t_1}$ but not $v_{4-5}^{t_1}$. If the returned states for r^{s_1} is $H^{s_1} = \{v_3^{t_1}, \mathrm{UC}_{4-5}^{t_1}\}$, then r^{s_1} maintains consistency because H^{s_1} belongs to V^{t_1}.

Note that consistency in transactional panorama is different from traditional Consistency (C) in ACID for database transactions. C in ACID refers to the property that each transaction correctly brings the database from one valid state to another. In our context, consistency is more closely related to Isolation (I) in ACID, which defines when view results created by one transaction can be read by others. Our notion of consistency allows a read transaction to read uncommitted results from a concurrently running write transaction (e.g., reading the uncommitted G^{t_1}), but additionally maintains the semantics that the returned states correspond to a single version.

A follow-up question about preserving consistency is which version of view graph a read transaction should read. Specifically, since we process one write transaction at a time, a read transaction can choose between reading the last committed version of view graph, which we call the *committed graph*, and the version that the latest write transaction is computing, which we call the *latest graph*. Depending on the version that is read, we define three types of consistency, which opt for different trade-offs between invisibility and staleness. (Recall that invisibility refers to the time during which the views in the viewport are invisible, while staleness refers to the time during which the returned view results are not consistent with the latest graph; both will be defined in Section 2.7.)

The first type of consistency is **Consistency-fresh** or C_f, which always reads the latest graph. C_f returns fresh results but suffers high invisibility. For the example in Figure 4, with C_f, read transactions always read G^{t_1} while we are processing the write transaction.

Another type of consistency, called **Consistency-committed** or C_c, always reads the most recently committed graph. C_c does not have invisible views, but the staleness of the returned view results could be high. In Figure 4, if C_c is used, read transactions cannot read G^{t_1} until we have computed all of the view results for G^{t_1} (i.e., $v_1^{t_1}$ and $v_{3-6}^{t_1}$).

We additionally introduce a type of consistency that lies between C_f and C_c. This type of consistency requires that a read transaction read the most recent version of the view graph that returns the minimum number of UCs for this transaction, which we call **Consistency-minimal** or C_m for short. With C_m, we would typically read the committed graph to avoid returning UCs when the new view results in the viewport are not yet computed. Once they are computed, we can read the latest graph to return fresh view results. Consider reading n_{3-5} in Figure 4. Initially, the read transactions will read G^{t_0} because G^{t_0} does not include UCs. After the new results for n_{3-5} are computed, we will read G^{t_1} because reading G^{t_1} for n_{3-5} does not return UCs, and G^{t_1} is more recent than G^{t_0}. Note that C_m is different from C_c because for C_c, read transactions will read the latest graph G^{t_1} after the write transaction is committed, while for C_m, read transactions will read G^{t_1} after all of the new results in the viewport are computed, which could be sooner. In addition, when the user changes the viewport, the minimum number of UCs returned by a read transaction may not always be zero for C_m. As we prove next, adopting C_m may sacrifice visibility if we need to additionally maintain monotonicity.

Correctness and Performance. Among the MVC properties, both monotonicity and consistency impact correctness, i.e., maintaining one or both of these properties may be essential to guaranteeing correct insights from the visual interface, depending on the application. The former ensures that users are not deceived by updates that get "undone", while the latter ensures that users viewing multiple visualizations on a screen can draw correct joint inferences based on the same snapshot of the source data. On the other hand, all of the MVC properties impact performance since maintaining these properties will increase staleness and/or invisibility as we will show in Section 2.8. Users can further make performance trade-offs between invisibility and staleness by choosing which version of the view graph to read for consistency.

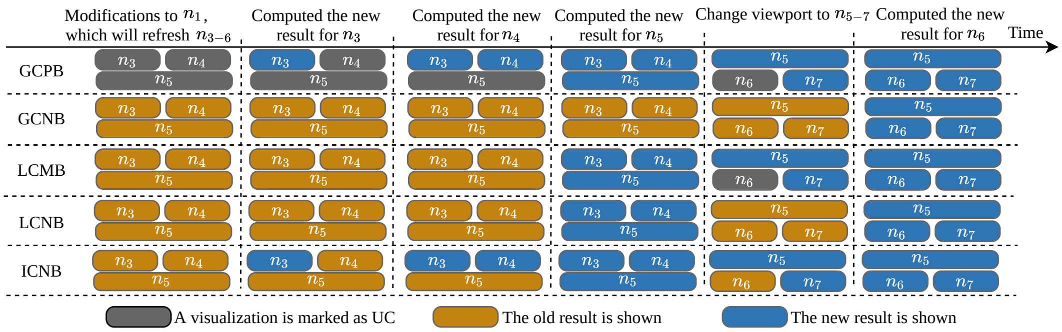


Figure 5: An example timeline for each lens presenting results to the user.

2.5 Feasibility of Property Combinations

We now develop a series of theorems, that we call the MVC Theorems, to characterize the complete subsets of MVC properties that can be maintained together. We omit some proofs due to space limitations, which can be found in the technical report [13]. Specifically, we define the possible property combinations involving each type of consistency (i.e., C_c, C_f, and C_m). The first two straightforward theorems establish the fact that always reading the committed graph provides monotonicity and visibility for free, while always reading the latest graph maintains monotonicity, but sacrifices visibility.

Theorem 1 (C_c). *Maintaining consistency-committed will also maintain monotonicity and visibility for read transactions.*

Theorem 2 (C_f). *Maintaining consistency-fresh will also maintain monotonicity for read transactions, but consistency-fresh and visibility cannot always be maintained.*

Unfortunately, with C_m, we cannot have both monotonicity and visibility: if two consecutive read transactions involve overlapping views, the latter transaction needs to read the same or more recent version of view graph compared to the former one to maintain monotonicity. Therefore, the latter transaction may read the latest graph, which may include UCs, thereby violating visibility.

Theorem 3 (C_m-impossibility). *We cannot always simultaneously maintain monotonicity, visibility, and consistency-minimal for read transactions.*

Proof. (Sketch) We construct a counterexample where the three properties cannot be met together. We assume the initial graph is G^{t_0} and a user modifies the base table n_1 in Figure 4. This modification creates a write transaction w^{t_1} that updates n_1 and n_{3-6}, and generates a new version G^{t_1}. We further assume we have computed the new results $v_1^{t_1}$ and $v_{3-5}^{t_1}$, but not $v_6^{t_1}$.

Based on this setup, consider two consecutive read transactions r^1 (reading n_{3-5}) and r^2 (reading n_{5-7}), which correspond to the case that the user moves the viewport. To maintain consistency-minimal, r^1 will read G^{t_1} and return $v_{3-5}^{t_1}$ since G^{t_1} does not include UCs for r^1. Now we show the subsequent transaction r^2 cannot maintain the three aforementioned properties simultaneously. To maintain monotonicity and consistency-minimal, r^2 has to read G^{t_1}. This is because both r^2 and r^1 need to read n_5, and r^1 has already read $v_5^{t_1}$ in G^{t_1}. However, reading G^{t_1} violates visibility because r^2 needs to read n_6 but $v_6^{t_1}$ has not yet been computed for G^{t_1}. This example proves that monotonicity, visibility, and consistency-minimal cannot always be met together. □

Interestingly, if we sacrifice one property among the three properties, we can always maintain the other two.

Theorem 4 (C_m-possibility). *Transactional panorama can always maintain any two properties out of monotonicity, visibility, and consistency-minimal for read transactions.*

2.6 Property Combinations and Lenses

Given the feasible property combinations, we now define different ways of presenting results to the user while preserving a given property combination, which we call *lenses*. We use Figure 5 to show illustrate how each lens presents results to the user for the example in Figure 4. In this example, the base table n_1 is modified, which will refresh n_{3-6}, but not n_7; the viewport initially includes n_{3-5} and is modified to n_{5-7} after we have computed the new view results for n_{3-5}. For simplicity, we use M for Monotonicity and V for Visibility.

Lenses from Theorems 1-2. We first define the lenses derived from Theorems 1-2:

- GCNB: Globally-Consistent Non-Blocking
- GCPB: Globally-Consistent Partially-Blocking

Theorem 1 shows that it is possible to preserve M-V-C_c together. We denote the lens for this property combination GCNB, which always reads and presents the view results from the recently committed graph to the user. On the other hand, lens GCPB preserves M-C_f based on Theorem 2. It always reads the latest graph, presents new view results that are consistent with the newly modified source data, and marks a view invisible if its view result has not been computed yet. Figure 5 has shown the examples for the two lenses presenting results in the visual interface. We include "Globally Consistent (GC)" in the names of the lenses GCNB and GCPB to indicate that for these two lenses all of the results (in the viewport or otherwise) are consistent with a single version of the view graph.

Lenses from Theorems 3-4. Next, we define the lenses derived from Theorems 3-4:

- LCNB: Locally-Consistent Non-Blocking
- LCMB: Locally-Consistent Minimum-Blocking
- ICNB: Inconsistent Non-Blocking

Lens LCNB adopts V-C_m from Theorem 4. Between the committed and latest view graphs, it reads the most recent version that does not have UCs for any read transaction, ensuring that each viewport does not have invisible views and that the results within a viewport are consistent. Lens LCMB adopts M-C_m from Theorem 4. Between the committed and latest view graphs, it reads the most recent version that returns the minimum number of UCs for each read transaction and preserves monotonicity. Specifically, if reading either the committed or latest graph preserves monotonicity, LCMB chooses the version that has the minimum number of UCs for the

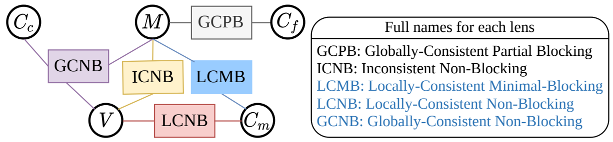


Figure 6: The possible property combinations and the corresponding base lenses covered in transactional panorama

read transaction, where the minimum number of UCs is zero since the committed graph includes zero UCs. Otherwise, LCMB reads the latest graph to preserve monotonicity, which may include UCs. Finally, lens ICNB preserves M-V. It allows a user to always inspect results of any views and refreshes each view independently, which sacrifices consistency. Figure 5 has shown the examples for the three lenses presenting results in the visual interface.

Discovering new lenses. We call the above lenses as *base lenses*, and their names and corresponding properties are summarized in Figure 6. GCPB is adopted by Power BI [8], Superset [11], and Dataspread [16], and ICNB is adopted by Google Sheets [2]. Recall that there is an existing lens, Globally-Consistent Fully-Blocking (GCFB), that is adopted by Excel [6], Calc [5], and Tableau [12]. It marks all of the views invisible until the system has computed all of the new view results. We don't consider it henceforth since it is dominated by GCPB. GCNB, LCNB, and LCMB are newly discovered lenses in our model.

***k*-relaxed variants.** As we will show in Figure 7, the three new lenses above are optimized to achieve low invisibility, but have high staleness. Therefore, we introduce their k-relaxed variants to allow for more invisible views to reduce staleness such that a user can gracefully explore the performance trade-off between invisibility and staleness, as visualized in Figure 2. Specifically, k-GCNB, the variant of GCNB, will read the latest graph if this graph involves k or fewer UCs, while GCNB reads the latest graph only when it is committed. Similarly, k-LCNB, corresponding to LCNB, reads the most recent version of view graph that has k or fewer UCs for the read transaction, ensuring the viewport has k or fewer invisible views. k-LCMB, the variant of LCMB, needs to maintain monotonicity and consistency, and works as follows. If reading either the committed or latest graph preserves monotonicity, k-LCMB reads the recent version that has k or fewer UCs for the read transaction, similar to k-LCNB. Otherwise, k-LCMB reads the latest graph to preserve monotonicity.

2.7 Performance Metrics

With the different lenses defined, we now formally define the performance metrics: invisibility and staleness, for these lenses .

Invisibility represents the total time when the views read by a user are invisible. We adapt the metric from previous work [16] to our scenario of modeling reading the view graph as read transactions. We define I, the invisibility for a set of read transactions $R = \{r^{s_1}, \cdots, r^{s_m}\}$, as:

$$I(R) = \sum_{i=1}^{m-1} |H^{s_i}_{\text{UC}}| \times (Time(r^{s_{i+1}}) - Time(r^{s_i}))$$

$Time(r^{s_i})$ is the time during which r^{s_i} returns and $H^{s_i}_{\text{UC}}$ is the set of UCs in the returned view states. So $|H^{s_i}_{\text{UC}}| \times (Time(r^{s_{i+1}}) - Time(r^{s_i}))$ represents the time when the views read by r^{s_i} stay invisible between two consecutive read transactions.

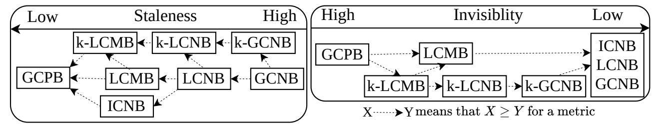


Figure 7: Summary of the orders across different lenses based on staleness and invisibility

Staleness represents the total time during which read transactions' returned view results are not consistent with the latest version of the view graph. We use S to denote staleness for a set of read transactions $R = \{r^{s_1}, \cdots, r^{s_m}\}$. Say G^{t_i} is the latest version of the view graph before the read transaction r^{s_i} starts, and say the returned view result by r^{s_i} for view n_k is $v_k^{t_j}$. S is defined as:

$$S(R) = \sum_{i=1}^{m-1} \sum_{v_k^{t_j} \in H^{s_i}_{qr}} \mathbb{I}[v_k^{t_j} \notin V^{t_i}] \times (Time(r^{s_{i+1}}) - Time(r^{s_i}))$$

Here, $H^{s_i}_{qr}$ represents the view results that are returned by r^{s_i}. $\mathbb{I}[v_k^{t_j} \notin V^{t_i}]$ is 1 if the view result is stale (i.e., $v_k^{t_j}$ does not belong to the latest version of the view graph); otherwise, it is 0. So the inner summation represents the total time when the view results returned by r^{s_i} stay stale between two consecutive read transactions.

2.8 Performance Metrics: Guarantees

Figure 7 plots the ordering across different lenses with respect to invisibility and staleness. Our analysis assumes the same write transaction, the same order of computing the new view results, and the same sequence of read transactions for all lenses. The theorems and proofs for guaranteeing the ordering can be found in the technical report [13].

3 MAINTAINING MVC PROPERTIES

We now discuss how to maintain different property combinations for different lenses defined in transactional panorama. Specifically, we discuss the design of the view graph and auxiliary data structures (Section 3.1), and the algorithms for maintaining MVC properties separately (Section 3.2-3.3) and maintaining property combinations for each lens (Section 3.4). We assume a *ReadTxn manager* responsible for processing read transactions, and another *WriteTxn manager* responsible for processing write transactions. The ReadTxn and WriteTxn managers are assumed to run on separate threads to enable concurrent execution of the two types of transactions. In Section 5, we discuss the strategy for triggering write transactions.

3.1 View Graph and Auxiliary Data Structures

We maintain a multi-versioned view graph. Each node stores a list of items, called *item list*, where a item could be a view result or UC, and created by a new write transaction. Recall that a UC is a place-holder for the corresponding view result. Each node in the view graph is associated with a latch to synchronize concurrent reads/writes to its item list.

We additionally maintain an auxiliary table, MetaInfo, to store the timestamps of the last committed and latest view graphs (denoted as t_c and t_s, respectively), and the number of UCs for the latest graph (denoted as c_{UC}). The quantities t_c, t_s, and c_{UC} are maintained by the WriteTxn manager and will be used by the ReadTxn manager to preserve the properties specified by the user. We also include a latch to synchronize concurrent accesses to the MetaInfo table, which means any access to MetaInfo needs to acquire this latch.

3.2 Maintaining Consistency

We now discuss preserving three types of consistency: C_c, C_f, and C_m, and will discuss preserving monotonicity and visibility separately in the next subsection. Intuitively, maintaining consistency for a read transaction means this transaction can read the recently committed and latest view graphs. However, traditional concurrency control protocols, such as 2PL or OCC [17], do not apply here because they do not support the type of consistency that reads an uncommitted version of the view graph (i.e., C_f and C_m). To maintain consistency, we process a read transaction in two steps:

1) Atomically find the timestamps for the last committed and latest view graphs (i.e., t_c and t_s in MetaInfo)
2) Read the versions of view graph for t_c and t_s.

Step 1) is done correctly via the latch on the MetaInfo table. Step 2) requires that the view graphs for t_c and t_s exist, which is done by the WriteTxn manager. Step 2) additionally requires an algorithm for reading a version of view graph for given a timestamp, which is done in the ReadTxn manager. We now discuss the designs of ReadTxn and WriteTxn managers for maintaining consistency.

WriteTxn manager. The WriteTxn manager processes a write transaction w^{t_i} in three steps:

1) Create a new version of view graph for w^{t_i}
2) Compute the view results for the views involved in w^{t_i} and update the view graph with the new results
3) Update t_c with t_i

Step 1) guarantees that the timestamp of the latest view graph, t_s, exists. Specifically, the WriteTxn manager creates a new version of view graph by appending UCs to the item lists of the nodes that w^{t_i} needs to update[3]. Then it atomically updates t_s with the timestamp of the running write transaction w^{t_i}, and c_{UC}, the number of UCs for the latest graph, in MetaInfo. Step 2) computes the view result and replaces the corresponding UC for each view, and updates c_{UC}. It leverages a scheduler to decide the order of computing the view results to reduce invisibility and/or staleness, which we discuss in Section 4. Step 3) updates the timestamp of the last committed version (i.e., t_c) with t_i, which guarantees that the version of view graph for t_c exists. We say w^{t_i} is committed if we have successfully performed the aforementioned three steps for w^{t_i}.

ReadTxn manager. The ReadTxn manager uses timestamps t_c and t_s to read the last committed and latest view graphs. Depending on the properties that need to be maintained, the ReadTxn manager decides the version to read, which is discussed in Section 3.4. Here, we present the algorithm for reading a version of view graph. Assuming a transaction r^{s_j} needs to read G^{t_i}, the intuition is that for each view read by r^{s_j}, we read the recent view result/UC whose timestamp is no larger than t_i. The reason is that we have two possible cases if a view result/UC for a node n_k belongs to G^{t_i}: 1) n_k is or will be modified by w^{t_i}, in which case we have a view result/UC whose timestamp is t_i; 2) n_k is not modified by w^{t_i}, in which case the most recent view result whose timestamp is smaller than t_i belongs to G^{t_i}.

[3] For GCNB and ICNB, which do not need to read the uncommitted version, we can skip generating UCs as an optimization

3.3 Maintaining Monotonicity and Visibility

To guarantee monotonicity, in the ReadTxn manager we maintain a table (denoted as *LastRead*) that stores the timestamps of the view results or UCs that are last read. Monotonicity requires that a read transaction reads the view results or UCs whose timestamps are no smaller than the corresponding timestamps in the LastRead table. To maintain visibility, we guarantee that the view states returned by a read transaction do not include UCs.

3.4 Maintaining Property Combinations

For the lenses that need to maintain consistency, we read the MetaInfo and LastRead table to decide which versions of the view graph to read. Specifically, to maintain M-C_f for GCPB we use t_s in MetaInfo to read the latest graph. Similarly, to preserve M-V-C_c for GCNB, we use t_c to read the last committed graph. For k-GCNB, we need to check whether the number of UCs for the latest graph (i.e., c_{UC} in MetaInfo) is no larger than k. If so, we read the version for t_s, otherwise, t_c is used.

Maintaining V-C_m for LCNB will read both the last committed and latest view graphs. Among the two sets of returned view states, we choose to return the set that does not have UCs and corresponds to the more recent version. Maintaining M-C_m for LCMB requires preserving monotonicity. This is done by checking the LastRead table to see whether reading the committed version violates monotonicity. If not, LCMB follows the same procedure of LCNB. Otherwise, LCMB will read the latest graph. k-LCNB and k-LCMB are processed similarly with k UCs relaxed.

For the property combination M-V (adopted by ICNB), which sacrifices consistency, we do not need to read MetaInfo. Instead, we directly read the view graph and return the most recent view result for each node involved in the read transaction.

4 WRITE TRANSACTION SCHEDULER

We analyze two factors that impact the performance of the scheduler and design a scheduling algorithm that considers these factors to reduce invisibility and staleness. Our discussion assumes processing a write transaction w^{t_i} that updates a set of nodes $N_w^{t_i}$.

Factors that impact invisibility and staleness. Staleness (or invisibility) is increased if a view that is read by a user is stale (or invisible), respectively. Therefore, prioritizing computing new results for views that a user will spend more time reading will best reduce the values of the two metrics. Since it is impossible to exactly predict how long the user will spend reading a view, we use $D_k^{t_i}$, the total time during which a view n_k has been read in the viewport since the write transaction w^{t_i} started as a proxy. Using $D_k^{t_i}$ is based on the assumption that the user will spend more time on a view in the future if they spent more time on this view in the past. For a set of read transactions $R = \{r^{s_1}, \cdots, r^{s_m}\}$ after w^{t_i} is started, $D_k^{t_i}$ is defined as

$$D_k^{t_i} = \sum_{j=1}^{m-1} \mathbb{I}[n_k \text{ is read by } r^{s_j}] \times (Time'(r^{s_{j+1}}) - Time'(r^{s_j}))$$

$Time'(r^{s_j})$ is the time when the system receives the read transaction r^{s_j}. $\mathbb{I}[n_k \text{ is read by } r^{s_j}]$ is 1 if the view n_k is in the viewport when r^{s_j} is issued, otherwise 0. Therefore, $\mathbb{I}[n_k \text{ is read by } r^{s_j}] \times (Time'(r^{s_{j+1}}) - Time'(r^{s_j}))$ represents the duration when the view

n_k stays in the viewport between two consecutive read transactions. The system tracks the arrival time of each read transaction and the views that are read by this transaction to calculate $D_k^{t_i}$. In our scheduling algorithm, we prioritize scheduling the view that has higher $D_k^{t_i}$.

In addition, there is another factor that impacts the staleness and invisibility: the different amounts of time for computing the results for different views. Intuitively, prioritizing computing the new result for the view that has the least execution time will allow the user to read a fresh view earlier, which is also observed by previous work [16]. We use $Q_k^{t_i}$ to represent the amount of time for computing the new result for the view n_k while processing w^{t_i}. The view that has a smaller $Q_k^{t_i}$ should have a higher priority.

Scheduling algorithm. We design a metric $P_k^{t_i} = D_k^{t_i}/Q_k^{t_i}$ to decide the priority of a view n_k. $P_k^{t_i}$ captures the characteristics of the two aforementioned factors. If two views have the same $D_k^{t_i}$, a lower $Q_k^{t_i}$ yields a higher $P_k^{t_i}$. Similarly, for the same $Q_k^{t_i}$, a higher $D_k^{t_i}$ results in a higher $P_k^{t_i}$.

The scheduling algorithm works as follows. We first sort $N_w^{t_i}$, the set of nodes w^{t_i} will update, topologically, break them into topologically independent groups, and compute each group with respect to the topological order. That is, we should only compute view results for views whose precedents are updated. To schedule a view to be updated within a group, we compute $P_k^{t_i}$ for each yet computed view n_k in this group and choose the view with the highest $P_k^{t_i}$.

5 PROTOTYPE IMPLEMENTATION

We now discuss implementing the transactional panorama framework in Superset [11], a widely used open-source BI tool. Superset provides a web-based client interface, where a user can define visualizations and organize them as part of a dashboard. The dashboard can be refreshed manually or configured to refresh periodically. Each refresh is interpreted as a write transaction. Superset adopts a web server to process front-end requests and employs a database to store the base tables and compute new view results for visualizations. The details of the prototype can be found in the extended version [13].

6 EXPERIMENTS

The high-level goal of our experiments is to characterize the relative benefits of different lenses for various workloads—to help users select the right lens for their needs and make appropriate performance trade-offs (Section 6.1). Our experiments also seek to demonstrate the value of the new lenses, which provide new trade-off points for the user to select (Section 6.1-6.2), and evaluate the performance benefit and overhead of the optimizations for the write transaction scheduler (Section 6.3).

Benchmark. We build a dashboard based on the TPC-H benchmark. This dashboard includes 22 visualizations for all of the 22 TPC-H queries and runs on 1 GB of data stored in PostgreSQL. This dashboard places two visualizations in a row, as in Figure 8. We test one refresh of the dashboard with respect to modifications to the base tables unless otherwise specified, since the main focus of this paper is on the scenario where there is only one write transaction in the system at a time. This case happens when the period for triggering a refresh is longer than the time for executing the refresh, or if the system only processes one refresh at a time. For the test of one refresh, we insert 0.1% new data to the tables Lineitem, Orders, and PartSupp and then refresh all of the 22 visualizations. One test ends when we have computed the new view results for all visualizations.

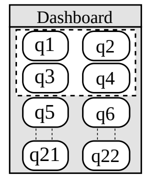
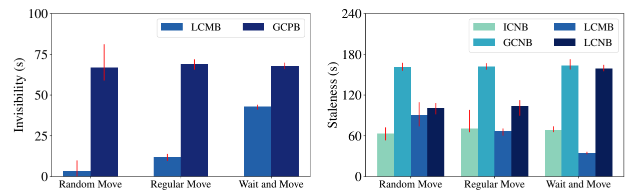


Figure 8: TPC-H dashboard

Configurations	Options	Default Value
Read behavior	{Regular Move, Wait and Move, Random Move }	Regular Move
Explore range	{22, 16, 10, 4}	22
Viewport size	{4, 10, 16, 22}	4

Figure 9: Experiment configurations



(a) Invisibility **(b) Staleness**

Figure 10: Evaluations of different read behaviors

We build a test client to simulate different user behaviors and dashboard configurations. Similar to the web client of Superset, this client sends web requests to the web server to trigger a refresh (i.e., start a write transaction), configure the lens used for processing a refresh, and regularly pull refreshed results of visualizations in the viewport (i.e., start read transactions). We simulate three types of user behaviors in moving the viewport to read different visualizations, which we call the *read behavior*: 1) *Regular Move*: regularly moving the viewport downward or upward and reversing the direction if we reach the boundary of the dashboard; 2) *Wait and Move*: similar to the first one with the difference that it only moves the viewport after all of visualizations in the viewport are refreshed; and 3) *Random Move*: randomly chooses a viewport, which simulates the behavior where the user moves around a lot in the dashboard. For the three behaviors, the viewport is placed at the top of the dashboard at the beginning of each test and moved every 1 second. For the first two behaviors, each move changes the viewport by a row of visualizations. The test client can additionally vary the number of visualizations the user will inspect in the dashboard (denoted as *explore range*) during a test. We assume these visualizations are at the top of the dashboard. For example, explore range 4 means that the user will explore the visualizations for q_{1-4} in Figure 8 during a refresh. Our experiments also vary the number of visualizations in the viewport (denoted as *viewport size*) to evaluate how the relative sizes of the viewport and the dashboard impact invisibility and staleness. The experiment configurations are summarized in Figure 9 and we use default configurations unless otherwise specified.

Configurations, and measuring invisibility and staleness. The experiments are run on a t3.2xlarge instance of AWS EC2, which has 16 GB of memory and 8 vCPUs, and uses Ubuntu 20.04 as the OS. Our experiments use PostgreSQL 10.5 with default configurations.

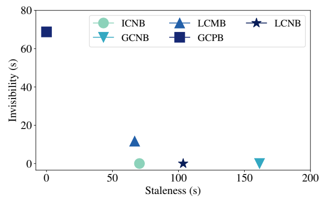
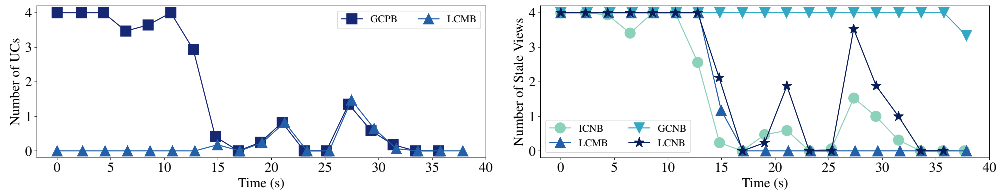


Figure 11: Performance trade-off for Regular Move



(a) Invisibility **(b) Staleness**

Figure 12: The number of invisible and stale views in the viewport during the refresh

The time interval between two consecutive read transactions is set to be 100 ms to avoid overwhelming the web server. that is, the test client sends requests to pull refreshed results every 100 ms. We run each test three times and report the mean number except for the tests that involve Random Move. For those tests, we run each 10 times and report the min, max, and mean.

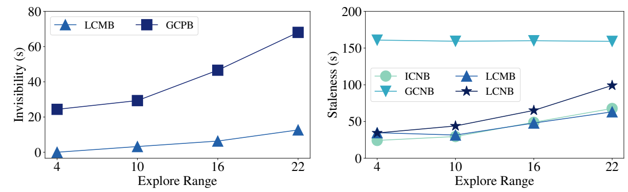
To measure invisibility and staleness, the test client tracks the timestamp when each read transaction returns and the content of the returned view states, which include information for whether each returned view state is a UC or a stale view result. Using this information and the definitions in Section 2.7, we can compute invisibility and staleness. For example, the invisibility for one test is initialized to 0. During the test, if a read transaction has returned a UC for a view, then the time difference between when this and the next read transaction return will be added to the invisibility.

6.1 Performance of Base Lenses

We evaluate the configurations in Figure 9 for the base lenses using one refresh. Afterwards, we test the impact of varied refresh intervals for multiple refreshes.

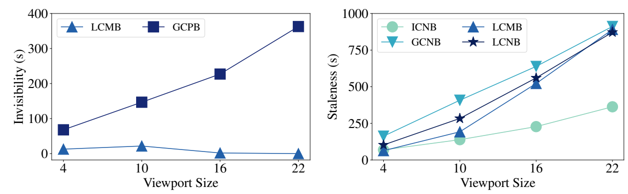
Read behavior. Figure 10 reports the invisibility and staleness for the base lenses under different read behaviors. Each test reports the mean with the min/max as the error bar (i.e., the red line). We note that if the invisibility or staleness for a lens is zero, then that lens is not shown in the figure. To better see the trade-off between invisibility and staleness, we also plot the two metrics together in Figure 11 for Regular Move. We observe significant differences in invisibility and staleness for different lenses in Figure 10—the new lenses (i.e., LCMB, LCNB, and GCNB) can significantly reduce invisibility while maintaining consistency compared to the existing lens GCPB. Specifically, GCPB has the highest invisibility because it always reads the latest graph, and LCMB, the lens that first reads the committed graph and switches to read the latest graph, can reduce invisibility by up to 95.2% compared to GCPB (i.e., Random Move). LCMB reduces less invisibility in the case of Wait and Move because it spends a longer time on reading the latest graph. That is, after the first viewport, LCMB always reads the latest graph for the rest of the viewports. LCNB and GCNB have zero invisibility. Recall that LCNB always reads the version of view graph with zero UCs for the viewport to maintain consistency and visibility, but sacrifices monotonicity, and GCNB reads the last committed graph until all of the new view results are computed for the latest graph. ICNB also has zero invisibility, but sacrifices consistency.

On the other hand LCMB, LCNB, and ICNB can significantly reduce staleness relative to GCNB. For example, LCMB reduces staleness by up to 78.9% compared to GCNB (i.e., for Wait and Move).



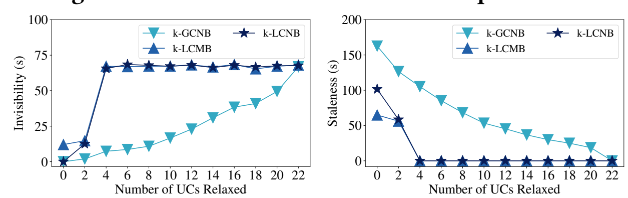
(a) Invisibility **(b) Staleness**

Figure 13: Evaluations of different explore ranges



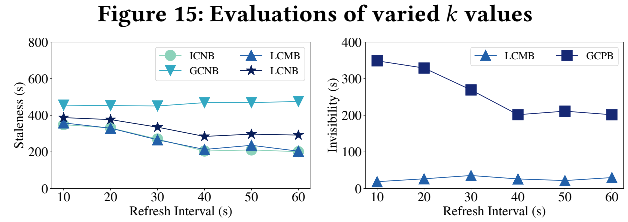
(a) Invisibility **(b) Staleness**

Figure 14: Evaluations of different viewport sizes



(a) Invisibility **(b) Staleness**

Figure 15: Evaluations of varied k values

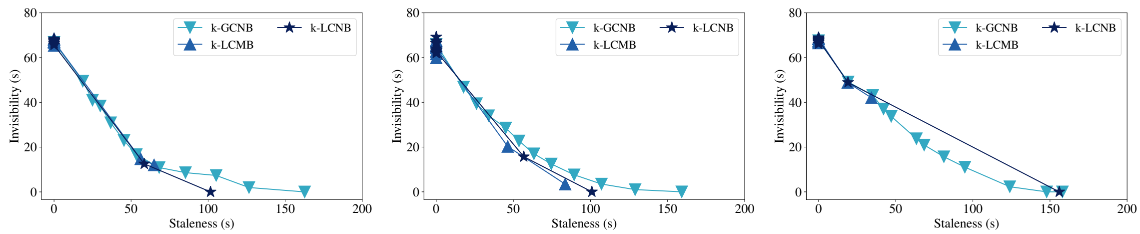


(a) Staleness **(b) Invisibility**

Figure 16: Evaluation of varied refresh intervals

LCMB reduces the staleness by sacrificing visibility while ICNB and LCNB need to sacrifices consistency and monotonicity, respectively. Overall, these results show that it is valuable to enable a user to have these options to make appropriate trade-offs. In addition, Figure 10b verifies the result that the order between ICNB and LCMB for staleness is undecided in Section 2.8—the staleness of ICNB can be either higher or lower than LCMB in Figure 10b.

To better understand the behavior of different lenses, we further report the returned number of invisible and stale views by read transactions for Regular Move while we are processing the write transaction. We aggregate the read transactions that finish for every 2s and report the mean in Figure 12. The areas under

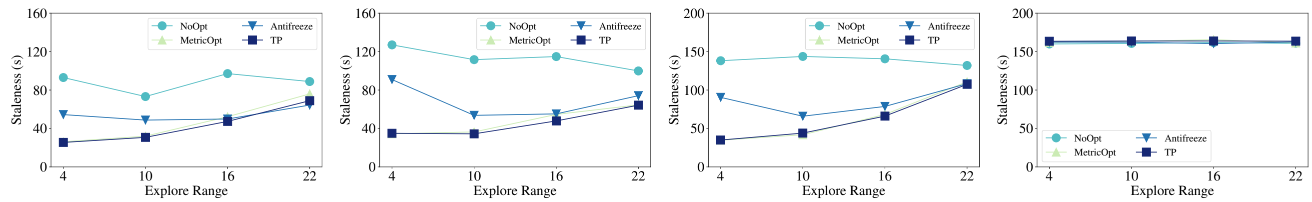


(a) Regular Move

(b) Random Move

(c) Wait and Move

Figure 17: Trade-off between invisibility and staleness with varied k values



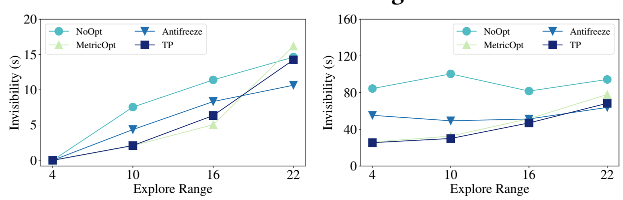
(a) ICNB

(b) LCMB

(c) LCNB

(d) GCNB

Figure 18: Evaluation of scheduler optimizations (staleness)



(a) LCMB

(b) GCPB

Figure 19: Evaluation of scheduler optimizations (invisibility)

the curve represent the invisibility/staleness in the respective figures. In Figure 12a, GCPB initially returns many UCs as it reads the new version, and the number of UCs decreases as we compute more view results. Specifically, for the first 10s, a user sees more than 3 UCs on average, out of the 4 visualizations in the viewport. Therefore, this user cannot interact for the first 10s, significantly diminishing interactivity. LCMB, on the other hand, initially reads the committed graph to avoid invisible views. Then, it reads the latest graph (i.e., after 15s) to present fresh results to the user as GCPB does. Figure 12b shows the number of stale views over time. GCNB reads the same number of stale views as the viewport size (i.e., 4 in our test) until the last transaction. LCMB, LCNB, and ICNB can read the new version during refresh, which reduces staleness.

Explore range. This experiment evaluates the impact of varied explore ranges on different lenses. The results in Figure 13 show that we have smaller invisibility/staleness for GCPB, LCMB, LCNB, and ICNB when the user explores a smaller number of visualizations because these lenses are more likely to read the new results for smaller explore ranges. The staleness for GCNB is independent of the value of explore range since it only refreshes the visualizations after all of the view results for the new version are computed.

Viewport size. Figure 14 reports the results of varying the viewport sizes. The invisibility for GCPB increases as viewport size increases because the user will read more invisible views for each read transaction. However, the invisibility for LCMB slightly increases and then decreases to zero. The reason for decreasing invisibility is that a larger viewport size pushes LCMB to wait longer to read the latest graph, which decreases invisibility. In an extreme case, when the viewport size covers the whole dashboard, LCMB's performance converges to GCNB, which has zero invisibility but the highest staleness, as shown in Figure 14b. The staleness for GCNB, LCMB, LCNB, and ICNB increases as they will read more stale views in one read transaction.

Refresh interval. We test three refreshes triggered periodically, where the interval between two succeeding refreshes (i.e., refresh interval) is varied from 10s to 60s. Same as the test for one refresh, before starting each refresh, we insert 0.1% new data to the database. We report the staleness and invisibility for different lenses. Figure 16 shows that a smaller refresh interval introduces higher staleness and invisibility when the refresh interval is less than the execution time for processing a refresh (i.e., 37s in our test) for all lenses except GCNB. This is because while a version of the view graph is being computed, a smaller refresh interval creates a new version of the view graph earlier. This leads the view results of the under-computation version of the view graph to become stale earlier, and, in turn the staleness and invisibility are increased. The staleness of GCNB is not impacted by the varied refresh interval because GCNB presents the up-to-date view results to the user when it finishes all of the refreshes in the system and its staleness is determined by the execution time for finishing multiple refreshes, which is independent of the refresh interval.

6.2 Performance of K-Relaxed Variants

We evaluate the impact of k for the k-relaxed variants; Recall that k represents the additional UCs permitted while reading the latest graph for LCMB, LCNB, and GCNB. Here, we vary the k from 0 to 22 with an interval of 2. Our results in Figure 15-17 show that the k-relaxed variants gracefully explore the trade-off between invisibility and staleness, and enable more trade-off points that are not covered in base lenses. Figure 15a shows that as we admit more UCs, the invisibility increases for the k-relaxed variants. However, when k becomes the same as or larger than the viewport size (i.e., 4 in our test), the invisibility does not change for k-LCNB and k-LCMB since they have converged to GCPB. However, staleness decreases as we have a larger k as shown in Figure 15b.

Figure 17 shows the trade-offs between invisibility and staleness under three read behaviors. We see that the k-relaxed variants have different trade-offs for different read behaviors. For example, for Regular Move in Figure 17a k-LCNB has better trade-offs than k-GCNB when the staleness is larger than 100s, meaning that for the same invisibility, k-LCNB has smaller staleness than k-GCNB. When the staleness is smaller than 100s, all of the three k-relaxed variants stay on the same trade-off curve. For Random Move, k-LCMB has the best trade-offs compared to the other two variants, and for Wait and Move, k-GCNB has the best trade-offs.

6.3 Effectiveness of Scheduler Optimizations

This experiment evaluates the benefit and overhead of the scheduler optimizations in transactional panorama (TP for short). We compare TP with three baselines: 1) NoOpt, after updating base tables randomly picking a view to compute, which is from Superset; 2) Antifreeze, from existing work that prioritizes computing the view with the least execution time [16], which is the second factor in TP's scheduling metric; 3) MetricOpt, which prioritizes computing the view that introduces the most invisibility plus staleness. Since the invisibility and staleness is increased only when a view is read, MetricOpt effectively prioritizes computing the view that the user spent the most time reading, which corresponds to the first factor in TP's scheduling metric (i.e., $D_k^{t_i}$). Recall that the effectiveness of $D_k^{t_i}$ depends on the property that a view that was read more in the past is more likely to be read in the future, which we call *temporal locality.* To study impact of temporal locality, we vary explore ranges and report staleness and invisibility for base lenses under different scheduling metrics.

Figure 18 shows that TP has smaller staleness compared to NoOpt and Antifreeze for all lenses. The performance benefit of TP over the baselines is larger when we have smaller explore ranges. Specifically, TP reduces staleness by up to 75% and 62% compared to NoOpt and Antifreeze, respectively. TP and the baselines have the same staleness for GCNB because GCNB refreshes the views after all of the new results are computed and its staleness is independent of a scheduler policy. Figure 19 shows that TP has smaller invisibility compared to NoOpt and Antifreeze in most cases. Similar to the results of staleness, TP has greater benefit when explore range is smaller except for LCMB with explore range 4. Here, the explore range equals the viewport size, so LCMB does not have invisibility. Overall, TP reduces invisibility by up to 70% and 54% compared to NoOpt and Antifreeze, respectively. However, TP may have higher invisibility than Antifreeze when the locality of reading the view graph weakens, such as for LCMB with explore range being 22. In this case, TP increases invisibility by 33%.

MetricOpt has similar results compared to TP since MetricOpt also prevails when there is strong temporal locality. However, when the locality weakens (e.g., the explore range is 22), TP has lower staleness and invisibility because TP additionally considers the different execution time for refreshing different views (i.e., the factor from Antifreeze). Specifically, TP reduces staleness and invisibility by up to 12% and 13%, respectively, compared to MetricOpt.

7 RELATED WORK

Our work is related to work in transaction processing, view maintenance and stream processing, and rendering results in interfaces.

Transaction processing. There is a long line of work on improving the performance of transaction processing while maintaining guarantees such as serializability or snapshot isolation [15, 19, 20, 26, 29, 34, 36, 38, 40]. However, none of these projects consider maintaining consistency while reading uncommitted results or other desired user properties in visual interfaces, such as visibility and monotonicity.

View maintenance and stream processing. Many papers propose various efficient incremental view maintenance algorithms [14, 21–23, 25, 30, 35, 42]. These techniques are orthogonal to our model and can be used to improve performance. Some papers explore the intersection of stream processing and transaction processing [18, 24, 27, 43]. Transactional panorama is different from these papers because they do not consider the user's semantics of consuming the results in a visual interface along with properties such as monotonicity and visibility.

Rendering analysis results in a visual interface. As summarized in Table 1, many existing data analysis tools make fixed choices on the properties maintained while rendering analysis results with respect to an update. Interaction Snapshots [37] additionally presents a scaled-down display of the dashboard for each interaction (e.g., cross-filter), where this scaled-down version serves as the new snapshot, with an indicator for whether the new snapshot is computed. This way, the user can interact with the old snapshot and replace it with the new snapshot later, similar to GCNB. However, Interaction Snapshot does not allow a user to read uncommitted results and choose the different properties they desire. Another line of research renders approximate results [28, 31, 32, 39, 41] and refines them later; we don't use approximation.

8 CONCLUSION

We introduced transactional panorama, a framework that explores the fundamental trade-offs between monotonicity, consistency, and visibility when a user examines results in a visual interface under updates. We identified feasible property combinations—and their lenses—based on the MVC Theorems, as well as new performance metrics, following it up by proving ordering relationships between various lenses for the metrics. We additionally designed new algorithms for efficiently maintaining different property combinations and processing updates. We implemented transactional panorama and its constituent lenses in a popular BI tool, Superset. Our experiments demonstrated significant performance differences across our lenses for various workloads, illustrating the benefit of our framework and newly discovered property combinations. We believe our transactional panorama framework is the first step in a new research direction around *bringing transactional notions to end-user analytics/BI*, with a human continuously "in-the-loop".

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